Value Creation and Competition in the Grocery Delivery Market

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Dedication

To my mom and dad.

Abstract

This dissertation contains three chapters, each of which is pertinent to the topic of how value is created to consumers and platform competition in the same-day grocery delivery market. All chapters make use of tools from empirical Industrial Organization. All data describing choices made by consumers used for both empirical evidence and demand estimation presented in chapters 1 and 2, respectively, pertain to the Nielsen Company (US), LLC and marketing databases provided by the Kilts Center for Marketing Data Center at The University of Chicago Booth School of Business. In the first chapter, I use the roll-out of two major same-day delivery services in several metro areas in the United Stated to study the impact of these new alternatives on consumers' retailer choice. To do so, I construct a new dataset with the timing of entry decisions of two grocery delivery platforms combine this geographic entry information with scanner data on consumer purchases to evaluate how store choices change once these new services are introduced. To measure the importance of user switching costs, in the second chapter, I estimate a demand model where consumers incur costs to update their delivery platforms choices over time. I extend Katz (2007)'s store choice model to a dynamic setting where, in addition to choosing bundles of products and retailers, consumers also pay a sunk cost to subscribe to memberships that augment their choice set of online retail alternatives. In addition to the revealed preference relations used in Katz (2007) which identify utility parameters, I estimate costs associated with subscriptions (fees and switching costs) using a second set of moments. I construct these moments using revealed preference conditions which compare the utility of maintaining the consumer's subscription choice to the utility of switching. To estimate switching costs, I use constraints that impose rational switching behavior identifying bounds on differential continuation values between subscriptions. I present evidence that switching costs are substantial: fewer than 50% of customers switch to a competitor in the face of savings of up to $40 per purchase. Using the model, I find that switching costs significantly affect consumer platform use. In the absence of switching costs, consumers would alternate between platforms from one purchase to the next ten times more often. By itself, this suggests a potential harm from the major firm's acquisition as lock-in would allow the combined firm to exercise market power in the future. In the third chapter, I model firm decisions as a dynamic entry game in which consumers' transition across platforms, predicted by the estimated demand model, governs the law of motion of firm revenues. Firms then compete in continuous time across independent markets in a similar fashion to Arcidiacono et al. (2016). I use this empirical framework to conduct a retrospective analysis of this recent acquisition. I show that an important aspect of the welfare impact of Big Tech's acquisition of

the national grocery chain was Grocer Partner's strategic entry response. Big Tech's main rival could have responded to the merger by either conceding or entering markets more rapidly. When met with the competitive threat presented by the merger, Grocer Partner's own intent to build a loyal customer base increases this firm's incentive to chase a first-mover advantage by entering new geographical markets earlier. Moreover, because Grocer Partner's entry costs are low, this firm is able to pursue this accelerated entry strategy giving rise to fierce competition for new markets. I find that the acquisition significantly increased both firms' speed of entry cross new markets, giving consumers earlier access to the services and generating important welfare gains in the short run. Specifically, had the acquisition not happened, both firms would have entered new markets over two years later, on average. The combined costs associated with the two firms' earlier entry due to the acquisition amount to a loss of $624 M in producer surplus. However, consumer benefits across markets that were served earlier due to this merger are larger, representing a total welfare gain of $846 M. Additionally, the fact that this merger allowed the large online retailer to enter multiple markets earlier provides an explanation for the premium paid for the acquisition. Moreover, until this merger occurred, this retail chain was Grocer Partner's largest affiliated retailer, giving it access to approximately 23 million consumers. This supports the fact that Grocer Partner anticipated how the acquisition would affect its ability to serve certain markets and reacted through earlier entry. I perform a second counterfactual that simulates a potential horizontal merger between Big Tech and Grocer Partner resulting in a monopoly. I find that, due to the lack of significant competitive threat, the monopolist would not have an incentive to serve markets early. This shows the role of competition in the timing of entry of these services. I also show that consumer losses due to delayed entry by the monopolist are larger than cost savings from this merger. In both analysis, the focus is on entry timing and firms do not choose prices in the model. For this reason, this paper is limited in its ability to capture possible future harm to consumers through prices. However, I use the demand model to show how consumers' substitution patterns as response to price changes under switching costs shed light onto issue. I find evidence that competition is important to keep prices low, especially if the firm' business model relies on economies of scale. This paper contributes to the literature on the role of consumer inertia in competition by measuring the importance of switching costs for entry strategies in a nascent market and highlighting the implications of this mechanism for consumer welfare. There is a large body of literature relating switching costs to price competition. There is also a theoretical literature relating switching costs to other dimensions of firm strategic behavior, including entry decisions: Klemperer (1988), Farrell and Shapiro (1988), Klemperer (1995), Farrell and Klemperer (2007), Klemperer (1987) and Schmidt (2010). Furthermore, switching costs are deemed theoretically important for preserving advantages to early movers: Lieberman and Montgomery (1988), Shapiro and Varian (2000), Amit and Zott (2001). However, the implications of switching costs for entry decisions have been studied less extensively empirically and measurement of first-mover advantages is sparse (Gómez and Maícas (2011)). This paper also relates to the literature measuring the importance of entry timing to firm decisions. In my setting, the source of early entry incentives is explicitly present in the demand model. I model the mechanism driving consumers' inertia and its relationship with firms' strategic behavior. There is a vast theoretical work on this topic since the early technology diffusion literature (Reinganum (1981a)), (Reinganum (1981b)) and (Fudenberg and Tirole (1985)). The empirical literature on this issue is much sparser due to the difficulty to single-out the motive driving timing from other sources of strategic behavior.

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Chapter 1

The Grocery Delivery Market: New Data on Services' Entry Patterns and Consumers' Choice Patterns

1.1 Introduction

In this section, I provide relevant details about the same-day delivery market. There is a large variety of delivery services, most of which specialized in grocery delivery. Most of them are constrained to one region of the US, concentrated in not more than a handful of large metropolitan areas. The two services that are studied in this paper have a nation-wide presence and, at the same time, a speed of delivery in the order of hours. This nation-wide scale makes the geographic richness of the data on entry patterns of the two firms and consumer choices quite unique.

Typically, grocery delivery services have subscription plans. Costumers pay a yearly or monthly flat-rate fee and get unlimited deliveries for that period. There is, however, a lot of heterogeneity in business models. A lot of services deliver only from one large brick-and-mortar retailer. Examples of large retailers that have their own delivery service include Walmart, Costco and, more recently, Target and Sam's Club. Many smaller grocery chains also offer their own delivery or pick-up services. Another type of delivery service business model are online platforms that specialize in fulfillment and operate through partnerships with multiple local stores. Examples include: Instacart, Peapod and Google Express. Finally, there are delivery platforms that are typical online retailers operating centralized distribution systems, making deliveries from a warehouse. This is the case for Amazon's Prime Now and Amazon Fresh as well as Jet.com. The firms studied in this paper represent two of these distinct business models: Grocer Partner operates through partnerships with local stores and Big Tech is a traditional online retailer with specialized distribution centers. Both have subscription services. Big Tech's subscription is bundled with a multitude of other services offered by the same online retailer and is a pre-requisite to use the service. However, Grocer Partner can be used without a subscription at the cost of a per-trip fee. For both services, annual fees range between $100-150 and Grocer Partner's trip-based fees range between $5-8. The actual cost of the service will depend on whether the household has a subscription or not. Since that information is missing for the households in my sample, I approximate the cost of Big Tech dividing the yearly cost of the subscription by the average number of trips made by users in a year. For the Grocer Partner firm, I use the trip-based fee. Those two fees are included in the cost of the bundle when estimating the demand model in chapter (2).

1.2 Data

To study competition between same-day grocery delivery platforms, I use data on their geographical roll-out since they were each first launched. Two firms stand out in this market both due to the fact that they have polar opposite cost structures and because they are by far the largest firms in terms of U.S. population coverage (figure B.13). These firms compete in many markets across the country (figure B.10) and their entry patterns reflect their strategic considerations relative to the other. *Big Tech* is the first firm: a traditional online retailer building logistical operations for groceries and sourcing products from its own newly built fulfillment centers dedicated exclusively to same-day grocery delivery. *Grocer Partner* is the second: an independent two-sided platform with massive geographic coverage and sourcing products from its grocery store partners[1]. The business model differences between *Big Tech* and *Grocer Partner* translate into important cost structure differences. The former incurs large entry costs associated with each new fulfillment center (FC) and, for this reason, should benefit significantly from returns to scale. Meanwhile, the latter incurs very low entry cost as partner stores are already established prior to entry in each market. These cost structure differences are important for the entry strategies available to each firm and for how the mergers studied in this paper impact competition and consumer welfare.

The first data source used in this paper is the Nielsen Consumer Panel Dataset (Homescan).

[1] In 2017, this firm's service was available to 70% of the U.S. population. This is calculated directly using the availability by zip code scraped from their website and Census data on population by zip code.

This is a transaction-level dataset that spans 2004-2016, including around 60,000 households annually. For each shopping trip made by panelists, there is detailed information on the products purchased - including UPC code and description as well as price paid. Panelists also report the retailer, the location of the store visited and the type of store (e.g. Grocery, Department store, Online Shopping, Discount Store and Drug Store). The data also includes household characteristics such as income brackets, presence of children in the household, age and education of heads of household, city and zip code.

I use a variety of data sources to construct a panel of availability of the two delivery services over time and by zip code. The first source is public information available on the official websites of both online platforms. I test over 20,000 zip codes on these websites to get the set of zip codes served, once the service is available in a given metro area. To recover the exact launch dates for each metro area, I collect several press releases, newspapers and scrape four years of posts on social media pages. *Grocer Partner* makes gradual expansions within the metro areas in the years after the first launch. For that reason, I use this firm's social media posts to recover the exact launch dates by neighborhood. With this, I construct a panel that spans 2012-2017 and includes all U.S. metropolitan areas entered by the platforms and tens of thousands of zip codes.

Finally, I match households in the Nielsen Homescan to the services' availability dataset using their zip code. Figures (B.11-B.12) show an example of the resulting delivery coverage by zip code for a metro area in the sample in 2015. To estimate demand, I work with 27 metro areas that include 680 zip codes served by *Big Tech*, corresponding to 4,708 households in the Homescan and, 640 zip codes served by *Grocer Partner*, corresponding to 4,693 households in the Homescan. A subset of these households are users of one or both services and their purchases through these new retail alternatives are observed in the data. The data used to estimate the model in chapter (2) includes all purchases from retailers *Big Tech* and *Grocer Partner* as well as a random sample of purchases made through other retailers by both users and non-users of the same-day delivery services.

I use the count of establishments by NAICS code for every zip code in the Zip Code Business Patterns 2016 (ZBP) for complementary information. The ZBP data are drawn from tax records, the U.S. Census Company Organization Survey, and other administrative data. I use it to construct the number of relevant retail alternatives within a 1 and 5 miles radius of each household by computing straight-line distances between the geocoded centroid of every zip code in the data and all other zip codes within those radius. Then, for every household zip code, I sum the number of retailers in the relevant NAICS codes located within those radius. These pair-wise distances between zip codes are also used to compute distances traveled by consumers to the stores they visit. The Homescan contains 5-digit zip codes for households but only 3-digit ones for stores, for privacy concerns. So, stores visited are assumed to be located the closest 5-digit zip code that starts with the 3-digits provided for that store in the Homescan.

Next , I show evidence that consumer choices are motivated by subscription timing and of the inertia associated with it followed by evidence of the firms' strategic interaction through entry timing.

1.3 Regression Analysis and Empirical Strategy

The empirical strategy presented in this section consists of exploring the before and after shopping behavior of households that gain access and use same-day delivery services. At the same time, non-users of the services within the delivery radius of the services and households in near-by zip codes that fall just outside of the delivery radius are used to control for time confounders.

1.3.1 Substitution of Offline Channels

In this section, I provide an empirical strategy to identify the causal effect of the availability of same-day delivery on households' choice of retail channel. The strategy consists in looking at the frequency of shopping trips to different types of retailing channels made by households who use the services Big Tech and Grocer Partner, before and after each service is launched. Figure (B.1) shows how the timing of when purchases from these new retailers first appear in the Homescan lines-up with the launch dates collected (time 0). For users of each service that are located in different metro areas, the date in which each service is made available will be different. Moreover, within the same metro areas, there are households located in adjacent zip codes where one of these zip codes falls within a service's delivery radius and the other does not. Hence, at a given period t, the sample contains: households that have access to one or two services and households that have access to none. The latter is divided between the two previously mentioned groups: households that will in some later period be served by Grocer Partner and/or Big Tech and households that will not but, live close to some that do. These two types of non-served households are used to control for time confounders that can be associated with oscillations in a retail channel's attractiveness in a given period. Meanwhile, the effect of interest is driven by changes in choices across retail channels for households that become users of the new services once they become available.

The regression analysis uses the same retail channels used to estimate the revealed preference model in chapter (2): Grocery Stores, Discount Stores and Drug Stores. Those are the most likely channels to be close substitutes to same-day online delivery services. The purpose of this exercise is twofold: firstly, to check the existence of a direct substitution between those channels and the new alternatives and, secondly, to point out shopping pattern differences that exist between households of distinct income levels.

The regression estimated is the following:

$$Pr(Channel_{it} = j) = \beta_0 + \beta_1 * \mathbf{1}_{GrocerPartner_{it}} + \beta_2 * \mathbf{1}_{BigTech_{it}} + \alpha_i + \alpha_t + \epsilon_{it} \tag{1.1}$$

An observation is a purchase made by household i in period t. The regression above is done for each channel type and income group separately. Hence, in each regression, the dependent variable is a dummy equal to 1 for each observation in the data corresponding to a shopping trip associated with that channel. I regress this dummy, for each channel and each income group, on two indicator variables: one for Big Tech and one for Grocer Partner firm. Each service indicator has to satisfy three conditions: the service has to be available in user i's metro area at time t, i's zip code has to be within that service's delivery radius and i has to be a user of that service[2]. Aside from these two variables of interest, all regressions include household fixed-effects and month-specific fixed-effects. Due to the high number of fixed-effects, I opt for a linear probability model instead of a non-linear approach such as Logit or Probit.

As previously mentioned, there are important differences in the delivery logistics used by each service and their relationship with offline retail. This translates into differences in the zip codes they choose to serve and the type of users they consequently have: table (B.13) shows how the demographic characteristics of delivery service users differ from the average Nielsen panelist in 2015-2016. The Grocer Partner firm, as it relies on the pre-existing retailing alternatives in an area, is most likely to enter zip codes that have more grocery stores, discount stores and drug stores. Those are also wealthier zip codes, as can be seen on table (B.5). Conversely, by having a centralized distribution system, the Big Tech firm serves a continuous radius centered in the downtown area of the cities it operates in: as shown in figure (B.4). This is more likely to include lower income neighborhoods, even if not purposefully. This is reflected on the characteristics of users: Big Tech firm has a larger share of users who are in the lowest income group ($< 45K$) than the Grocer Partner firm, as shown in table B.13. Moreover, as it is well documented in the food deserts literature, low income households are more likely to shop for groceries at drug stores and discount stores, instead of supermarkets or grocery stores. Whether the reason for this is differences in retail availability or differences in demand across income groups (as posed by Allcott et al.

[2]A household is defined as a user of a service if they have made a purchase through that service at any point in time.

(2018)), these features will result in substitution patterns that differ across income groups and the two new services. For this reason, the regressions presented show that channels more likely to be replaced by the new retail alternatives differ across groups.

The regression results are presented in tables (B.17) - (B.19). The coefficients on each firm's availability indicator represent the change in the probability that a user of that service buys from a retailer in channel j after the service is available. The launch of the Big Tech service has effects across all income groups and all three offline channels. Notably, the probability of a household in the lowest income group making a grocery trip falls by 35 percentage points once the delivery service is available. For the highest income group, the Big Tech service doesn't seem to be a close substitute for grocery trips. However, the Grocer Partner service is: users of this service in this income group make 33% less grocery trips once this service is available. Discount stores see a drop of 8-11% in trips across all income groups when the Big Tech service becomes available.

Finally, the logistic differences between Grocer Partner and Big Tech firm also impact their product selection. At least during the period between 2015 and 2016, even though Big Tech firm had a very large catalog of general merchandise as well as dry and frozen groceries, it had a very limited selection of fresh produce. Grocer Partner firm, however, had multiple partnerships with grocery stores, notably some of the largest in the country and some known for the quality of their fresh produce department. Given that high income households, even when shopping at the same retailer[3], buy 0.62 standard deviation more items in this category, Grocer Partner firm is a closer substitute for grocery shopping than Big Tech firm in this income group.

1.3.2 Distance to Retail and Use of New Services

In this section, I discuss the role of distance to offline retail as a determinant of demand for new online delivery services. There is large variation in the number retailers available through the Grocer Partner platform across locations as well as variation in how close consumers are to offline retail, including to stores that have a partnership with Grocer Partner (see figure (B.6)). I show how the probability of a consumer using new online delivery services depends on the distance to offline retail substitutes and, in the case of the Grocer Partner service, how offline partnered stores are - to some extent - complements. I use the number of stores within 1 mile of each consumer to measure the number of alternatives available and use distance to closest Grocer Partner partner store to identify the existence of substitution between the new service and the retailers it relies on. Since distance to partnered stores also determine availability of the Grocer Partner service and

[3] See tables (B.11) and (B.12)

the number of retailers the consumer can choose on this platform (see figures (B.7) and (B.8)), I also control for the number of partners offered through the Grocer Partner service in the consumer's zip code.

Table (B.20) shows the result of the linear probability regressions for Grocer Partner firm. In the most complete specification, the probability that a consumer makes a purchase using the Grocer Partner service depends on all the variables described above: distance to retail, number of Grocer Partner partners offered in the consumer's zip code and number of stores within 1 mile. The main endogeneity issue in identifying the effect of proximity to offline retail on use new online services is due to the fact both availability and quality of these new services can also depend on proximity of the consumer to stores. Indeed, controlling for the number of partners in the consumer's zip code impacts the coefficient on distance in the expected direction. According to the most complete specification, a consumer located at 5.6 miles from the closest Grocer Partner affiliated store is 0.68 percentage points (approximately 5 standard deviations) more likely to purchase from Grocer Partner firm than a consumer located within 1 mile. Any additional store (this includes only grocery stores, discount stores and drug stores) within 1 mile also impacts negatively the probability of purchasing from the Grocer Partner service (0.33 p.p. per store - 2.7 standard deviations). However, having more partners impacts the probability of purchase positively (0.37 p.p or 3 standard deviations per additional alternative offered). This means that zip codes that are located closer to partner stores are offered more alternatives within the Grocer Partner service and, are more likely to use this service for this reason but, the closer they are located to these stores, the less likely they are to use the online service.

Table (B.21) presents similar results for the Big Tech service. As this service does not rely on partnerships with local stores, it is strictly a substitute to brick-and-mortar retail. The number of Grocer Partner affiliates offered in a zip code and the proximity to Grocer Partner affiliated stores both seem to have no effect on the demand for the Big Tech service. However, the overall number of offline alternatives within 1 mile (0.32 p.p. or 1.8 standard deviations per additional alternative) and the proximity to overall brick-and-mortar alternatives both correlate to the probability of purchasing from the Big Tech service. An additional store within 1 mile reduces the probability of purchasing from the Big Tech service by 0.33 percentage points (approximately 1.8 standard deviations).

1.4 Consumer Lock-in

In this section, I show evidence that consumer choices are motivated by subscription timing and of the inertia associated with it followed by evidence of the firms' strategic interaction through entry timing.

Table B.32 shows the frequency of switching occurrences across platforms where an observation is a purchase. Switching patterns show that consumers rarely switch between services offered by different firms. In over 98% of purchases, consumers choose to use an alternative they have used recently. Only in 0.18% of purchases in the data consumers choose to buy from *Grocer Partner* when they have used a service provided by *Big Tech* in the last three months. Table B.33 shows the number of days after the first purchase using one of the two services it takes a switcher to switch. This table shows that the first time a consumer uses either service is likely to be when they first subscribe to that service. Indeed, switching, if it occurs, happens around what would be the expiration date of a monthly or yearly subscription, assuming the user subscribes when the use the service for the first time. Switching rates measured in each of these two manners are quite low, consistent with other sources of data[4]. Identification of the demand model also relies on variation in choices made by consumers across demographic groups and geographic characteristics. As previously mentioned, there are important differences in the delivery logistics used by each service and their relationship with offline retail. This translates into differences in the zip codes they choose to serve and the type of users they consequently have. As *Grocer Partner* relies on the pre-existing stores in an area, it is more likely to enter zip codes that have more grocery stores, discount stores and drug stores. Those also tend to be wealthier zip codes. Conversely, by having a centralized distribution system, *Big Tech* serves a continuous radius centered in the downtown area of the cities it operates in. This is more likely to include low income neighborhoods, even if not purposefully. This is reflected on the characteristics of users: *Big Tech* has a larger share of users in the lowest income group ($< 45K$) than the *Grocer Partner*.

In figure B.9 I show how switching behavior relates to price changes of the bundle purchased. I compute the difference between prices paid and prices at the alternative platform for consumers that have access to both choices. The figure maps price differentials against an indicator of switching associated with the individual and a smoothed outcome measure of the switching probability. Individuals that have purchased bundles with higher differential prices are more likely to eventually switch between platforms. This is preliminary evidence that switching is at least partially driven by prices and, therefore, rational. However, high price differences still predict a switching probability below 50%, indicating that small price differences are not enough to induce switching. Moreover, these differences in prices across retailers are an important source of variation identifying parameters in the model. These two facts indicate that price comparisons for the bundle chosen induce switching but, at the same time, consumers may also incur switching costs not captured by bundle

[4]No grocery delivery company shared more than 13% percent of another company's customers (2019): https://secondmeasure.com/wp-content/uploads/2019/08/GroceryDelivery-chart3_v2.png

price differences. These additional costs may be due to subscription sign-up fees or other non-monetary costs such as the time spend comparing prices across platforms. I do not distinguish between such types of costs in the demand model. Instead, I infer the combined sunk costs that rationalize switching behavior in the data in order to reproduce demand dynamics under the assumption that the price scheme is unchanged.

1.5 Evidence of Entry Timing as a Strategic Decision

In this section, I describe how entry and coverage patterns differ between the two firms and provide suggestive evidence of how they interact strategically. Figure (B.10) shows the presence of same-day grocery delivery services across the US in 2017.

As previously mentioned, the two platforms competing in the game presented in chapter (3) have very distinct cost structures. This is relevant to understand how they make use of different strategies impacting their speed of entry. *Big Tech* makes use of fulfillment centers dedicated to same-day grocery delivery. Before this platform is launched in a new location, it builds a new fulfillment center and traces a continuous delivery radius around it. *Grocer Partner* makes use of pre-existing stores belonging to retail partners. Figures (B.11-B.12) show how this impacts their geographic footprint. Whereas the former has a continuous coverage, the latter has often pockets of covered zip codes geographically close. These business model differences are relevant to understand the entry strategies each firm can make use of and their costs. *Big Tech*'s model is expected to lead to high entry costs and distribution costs that decrease significantly with population density. Conversely, *Grocer Partner*'s implies low entry costs, as no infrastructure needs to be built to operate. This also means that the speed with which each firm can make entry decisions is likely to be different. For example, if *Grocer Partner* believes *Big Tech* is likely to enter a certain market soon, it is more likely to enter early as a response if its entry cost is low. The evidence presented next is compatible with these features of the firms' costs.

The motivating evidence of the two platforms' strategic interaction uses the timing of the event in which *Big Tech* acquired a grocery chain. Around the time of the announcement, there is a spike in the number of *Grocer Partner*'s entry decisions across new markets, as shown in figure (B.16). Because this firm's business model relies on making use of pre-existing stores, its entry cost should be low. Consequently, it reacts to the rival's announcement immediately with entry across new markets where, with the acquisition, *Big Tech* is expected to enter sooner. Effectively, because the grocery chain had a multi-year contract with *Grocer Partner* at the time of the acquisition, *Big Tech* can only start making use of the newly acquired stores as delivery hubs six months after the acquisition. Figure (B.15) shows the faster rate of entry once the firm has its entry cost reduced by the acquisition.

This is the key motivating evidence for the first merger counterfactual conducted using the duopoly game. It shows that the timing of the firms' entry decisions and, in particular, their strategic interaction in this dimension can be important. Combined with the motivating evidence of lock-in, this justifies the choice of a model where forming a base of subscribers is a driving force of entry timing and where the consequences of a merger can be evaluated in terms of strategic entry timing. Moreover, in the model I allow for entry costs to vary over time to capture how firms' ability to grow may be evolving over time.

Chapter 2

The Demand Model: Combining Dynamic Subscription Decisions with Static Store Choices

2.1 Introduction

To measure the importance of user switching costs, I estimate a demand model where consumers incur costs to update their delivery platforms choices over time. I extend Katz (2007)'s store choice model to a dynamic setting where, in addition to choosing bundles of products and retailers, consumers also pay a sunk cost to subscribe to memberships that augment their choice set of online retail alternatives. In addition to the revealed preference relations used in Katz (2007) which identify utility parameters, I estimate costs associated with subscriptions (fees and switching costs) using a second set of moments. I construct these moments using revealed preference conditions which compare the utility of maintaining the consumer's subscription choice to the utility of switching. To estimate switching costs, I use constraints that impose rational switching behavior identifying bounds on differential continuation values between subscriptions. I present evidence that switching costs are substantial: fewer than 50% of customers switch to a competitor in the face of savings of up to $40 per purchase. Using the model, I estimate that switching costs range between $ 4 and $ 14 per purchase. These values include sunk costs associated with subscription fees which I estimate jointly with potential non-monetary switching costs to rationalize consumers' behavior. Overall, these costs represent the dollar value forgone by consumers who do not switch in the presence of lower prices for products at the alternative service. I find that these costs significantly affect consumer platform use: in the absence of switching costs, consumers would alternate between platforms from one purchase to the next ten times more often. By itself, this suggests a potential harm from the major firm's acquisition as lock-in would allow the combined firm to exercise market power in the future. This paper contributes to the literature on the role of consumer inertia in competition by measuring the importance of switching costs for entry strategies in a nascent market and highlighting the implications of this mechanism for consumer welfare. There is a large body of literature relating switching costs to price competition[1]. There is also a theoretical literature relating switching costs to other dimensions of firm strategic behavior, including entry decisions: Klemperer (1988), Farrell and Shapiro (1988), Klemperer (1995), Farrell and Klemperer (2007), Klemperer (1987) and Schmidt (2010). Furthermore, switching costs are deemed theoretically important for preserving advantages to early movers: Lieberman and Montgomery (1988), Shapiro and Varian (2000), Amit and Zott (2001). However, the implications of switching costs for entry decisions have been studied less extensively empirically and measurement of first-mover advantages is sparse Gómez and Maícas (2011).

2.2 Demand Model

Many grocery delivery services require a subscription membership payed monthly or yearly. This is the case for *Big Tech*'s grocery delivery service: consumers need a membership to a set of benefits and this subscription includes grocery delivery at no additional cost. *Grocer Partner* offers a yearly subscription membership that costs approximately $150 and includes unlimited delivery at no additional cost. Since consumers' subscription status are not directly observed, I infer it through purchases. Consumers in the data don't switch back and forth between the two services and multi-homing (using more than one platform simultaneously) is negligible in the sample. Consequently, I only consider the three mutually exclusive alternatives of consumer status: $s \in \{$*No Subscription (0), Big Tech (B), Grocer Partner (G)*$\}$. This variable is an indicator of whether the consumer has purchased from either firm in the past.

The demand model reflects the different aspects of consumer choice observed in the data. As an observation is a purchase decision for a panelist, there isn't a fixed period between choices. For this reason, I assume consumers receive utility shocks associated with products they might want to buy in continuous time. A purchase decision then occurs as a result. Conditional on a purchase being observed in the data, I model the consumer's utility over the observed and unobserved aspects of the decision: subscription, retailer and bundle of products chosen. I then use a revealed preference approach to identify the relevant sets of parameters.

[1]Some theoretical and empirical examples include Rosenthal (1982), MacKay and Remer (2019), Bagwell et al. (1997), Cabral (2012). For surveys, see Cabral (2016) and Miguel Villas-Boas (2015).

2.2.1 Consumer Problem

For each consumer i, consider a dynamic single-agent decision problem in which time is continuous and an arrival process governs when decision opportunities indexed by $t = 1, 2, ...$ are made. At any time, the state for i is the subscription status inherited from the last decision period $s \in \{0, B, G\}$. When a decision opportunity arrives, the consumer chooses to update the subscription s', conditional on the current state s and a random utility component ϵ. The individual also makes shopping decisions conditional on the updated subscription s' and ϵ. Shopping decisions are bundle $b \in \mathcal{B}$ and retailer $j \in J_{s'}$ choices with indirect utility:

$$U_{s'}(\epsilon) = \max_{\{b \in \mathcal{B}\}, \{j \in J_{s'}\}} u_{bj}. \tag{2.1}$$

The indirect utility is in the spirit of Katz (2007). There is a structural random utility component which is bundle, consumer and time-specific: ϵ. To not burden the notation, I omit all individual and time subscripts and discuss below which components are observed at the individual and time levels. The utility of purchasing a bundle of products b at retailer j is:

$$u_{bj} = V_b + (-1 + \alpha Y)P_{bj} + X_j(\beta_0 + Z\beta_1) + T_j(\gamma + \eta) + \epsilon_b, \tag{2.2}$$

P_{bj} is the expenditure required to buy b at j which is specific to purchase t and the price paid by the individual is observed. This includes any promotions i may have received to buy the bundle, which are observed in the data. The baseline price elasticity is normalized to be -1 which means that the remaining parameters are expressed in dollar terms. Additionally, the elasticity is allowed to differ according to the individual's income Y and the parameter α.

Z_1 are demographic variables which affect i's preferences for retailer characteristics X_j which are subsumed by a fixed-effect for each retailer. This fixed-effect provides an estimate for any differences in quality not captured by other observables[2]. The retailer fixed-effect controls are then used to address the price endogeneity issue associated with quality and evaluate how retailer preferences vary across demographic groups. T_j is the distance between i and retailer j's closest store, if j is a brick-and-mortar retailer. The utility of the bundle has one constant and one random component. V_b is the mean utility associated with the bundle of goods purchased. ϵ_b is the random utility component associated b observed by the consumer when making the purchase in t but, unknown to the researcher. Consequently, this error is

[2]This is a control for what would be the unobserved quality of the product ξ_j in a typical discrete choice setting.

a high-dimensional object defined over all possible products the consumer can buy $b \in \mathcal{B}$ in a decision period. Finally, η is a constant component of i's in travel cost also unobserved by the researcher and approached econometrically as random coefficient, as done in Katz (2007).

A1: *Unobserved preferences for bundles and retailers are separable.*
A1 is assumed in specification (2.2). This is same assumption imposed in Katz (2007) in order to perform the revealed preference approach to identify the parameters in (2.2). This means that retailer quality does not depend on the bundle purchased and can, therefore, be measured as a retailer fixed-effect. Even though retailer quality doesn't vary with b, prices vary across retailers, bundles and periods. If consumers have some information about prices before making decisions, this rationalizes the fact that consumers don't always buy the same things and from the same retailers. First, this means that the cheapest retailer for a particular bundle isn't the same across periods. Secondly, after considering both prices and other dimensions of retailer quality that are invariant across bundles, the optimal retailer choice can vary across periods. The problem solved by consumer during a decision period is then:

$$V(s,\epsilon) = \max_{s' \in S}\{u_{s'}(\epsilon) - C(s,s') + \beta\mathbb{E}[V(s',\epsilon')|s']\}, \tag{2.3}$$

Where $C(s,s')$ is a cost function which depends on the state and the subscription choice. The discount factor β combines the expected length of the random interval between the current trip and the next decision and the consumer's is the discount factor in continuous time. To compute the discount factor prior to estimating the demand model, I make an assumption about the arrival process of purchases and take the expectation over the random interval between purchases and the number of future trips[3].
The cost of subscription changes is assumed to be:

$$C(s,s') = \begin{cases} c_{BG}, & if \quad s = B \quad and \quad s' = G; \\ c_{GB}, & if \quad s = G \quad and \quad s' = B; \\ c_{0B}, & if \quad s = 0 \quad and \quad s' = B; \\ c_{0G}, & if \quad s = 0 \quad and \quad s' = G; \\ 0, & otherwise. \end{cases} \tag{2.4}$$

These transition costs are estimated without imposing that the length of subscription contracts is known. Consumers are always allowed to switch but, if they have status s, they

[3]More details in the Appendix.

pay a cost of choosing $s' \neq s$. Consequently, I estimate a cost which is a combination of monetary sunk subscription costs and any other non-monetary costs that user decisions may imply. I refer to the combination of these two types of costs as *switching costs.* These are sunk costs $c_{ss'}$ depending on which subscription $s \in \{0, B, G\}$ the individual held at the time of the service change to s'. Moreover, the cost of termination - choosing absence of subscription ($s' = 0$) - is always assumed to be zero for the identification reasons discussed in the next section.

2.2.2 Demand Identification: Revealed Preference

I first discuss the identification of utility parameters θ. I show there is a set of revealed preference relations that generate moments for these parameters which are identical to a setting such as Katz (2007)'s. I then derive the set of moments I use to estimate continuation values and subscription costs.

Identification of Utility Parameters

Suppose a consumer receives a decision shock in period t. They then choose (b, j) to solve equation (2.1). If the separability assumption **A1** holds true, we can compare the utility value associated with each alternative retailer $k \neq j$ such that $k, j \in J_{s'}$ holding the subscription and bundle chosen fixed. By holding the bundle fixed, the difference in utility across retailers is independent of the bundle chosen, reducing the set of parameters to be estimated. Moreover, by holding the subscription fixed, costs associated with maintaining or switching between subscriptions are differenced out along with continuation values. To see this, let b denote the bundle bought at retailer j and $\tilde{b}$ denote the optimal bundle the consumer would have bought at an alternative store k.

Let I be the individual's information set when making such decision. Suppose the state is s optimally makes a subscription decision s'. The revealed preference relation between the individual's choice and their utility when the optimal bundle $\tilde{b}$ associated with the alternative retailer choice k is:

$$\mathbb{E}[u_{bj} - c_{ss'} + \beta \mathbb{E}V(s', \epsilon')|I] \quad \geq \quad \mathbb{E}[u_{\tilde{b}k} - c_{ss'} + \beta \mathbb{E}V(s', \epsilon')|I], \quad \forall k \in J_{s'}. \tag{2.5}$$

Additionally, if $\tilde{b}$ is the optimal bundle choice at store k then, for any other bundle - including b - the following inequality also holds true:

$$\mathbb{E}[u_{\tilde{b}j} - c_{ss'} + \beta \mathbb{E}V(s', \epsilon')|I] \quad \geq \quad \mathbb{E}[u_{bk} - c_{ss'} + \beta \mathbb{E}V(s', \epsilon')|I], \quad \forall k \in J_{s'}. \tag{2.6}$$

By transitivity, joining the last two inequalities yields:

$$\mathbb{E}[u_{bj} - c_{ss'} + \beta \mathbb{E} V(s', \epsilon')|I] \quad \geq \quad \mathbb{E}[u_{bk} - c_{ss'} + \beta \mathbb{E} V(s', \epsilon')|I], \quad \forall k \in J_{s'}. \tag{2.7}$$

Note that both sides of this inequality have identical terms with the exception of u_{bj} and u_{bk}. Consequently, it simplifies to:

$$\mathbb{E}[u_{jb}|I] \geq \mathbb{E}[u_{k\tilde{b}}|I] \quad ie, \quad \mathbb{E}[\Delta u_{bjk}|I] \geq 0. \tag{2.8}$$

This last inequality is the key implication of consumer behavior used for estimation. It implies that, for any purchase (b, j), we can hold the bundle b and the subscription s' fixed and compare the utility of this observed choice with the utility of the alternative choice (b, k) as long as k is also a retailer available in $J_{s'}$. Re-arranging this result and using the specification from equation (2.1) we get:

$$\mathbb{E}[\Delta u_{b,jk}|I] = \mathbb{E}[(-1 + \alpha Y)\Delta P_{bjk} + \Delta X_{jk}(\beta_0 + Z_1\beta_1) + \Delta T_{jk}(\gamma_0 + \eta)|I] \geq 0. \tag{2.9}$$

Note that, not only are subscription costs and continuation values differenced out but, so are both terms associated with the bundle utility: V_b, the mean bundle utility and ϵ_b, the unobserved bundle shock. As as result, we have a set of inequalities that depends only on retailer choice utility parameters.

The measured moments that are used to estimate the vector of parameters θ of the utility are:

$$\Delta \tilde{u}_{b,jk}(s; \theta) = (-1 + \alpha Y)\Delta \tilde{P}_{bjk} + \Delta \tilde{X}_{jk}(\beta_0 + \tilde{Z}_1\beta_1) + \Delta \tilde{T}_{jk}(\gamma_0 + \eta) \geq 0, \tag{2.10}$$

ϵ is a *structural error* and ignoring this type of error can cause important bias[4]. Differencing out this term implies that these moments are valid regardless of the characteristics of this random variable which avoids problems with making additional specification assumptions. The term η is source of unobserved heterogeneity known to the consumer that can also be a source of bias if ignored. This term is addressed with a normalization with respect to the traveled distance for the trip (when it's offline). Details of this normalization can be found in Katz (2007). Another type of error that can arise in this setting is *measurement error*[5]. This includes expectational errors and other examples discussed next.

Measurement errors enter naturally in the model. This is the case for the expectational error that would arise if the incorrect bundle is used to measure equation (2.10). If the consumer

[4] This corresponds to the class of errors labeled as ν_2 in Pakes et al. (2015).

[5] ν_1 in Pakes et al. (2015).

based their purchase decision on bundle b' instead of b, an error of this sort would correspond to the difference between the expenditure for these two bundles: $\nu_1 = \Delta P_{bjk} - \mathbb{E}[\Delta P_{b'jk}|I]$. It should then be the case that $\mathbb{E}[\nu_1|I] = 0$ and, consequently,

$$\mathbb{E}[\Delta\tilde{u}_{bjk}|W] = \mathbb{E}[\Delta u_{bjk}|W] = \mathbb{E}[\Delta u_{b'jk}|I] + \mathbb{E}[\nu_1|I] = \mathbb{E}[\Delta u_{b'jk}|I] \geq 0, \tag{2.11}$$

Where $\tilde{u}_{bjk}$ is the difference in utility measured and W are the instruments used for the consumer's information set[6]. Further details on this type of expectational error can be found in Katz (2007).

Since current prices are observed in the data, the inequality (2.9) is measured directly from the data for a set of alternative retailers k that are good comparisons to choice j. For every purchase in the data, the counterfactual cost of the bundle purchased is constructed for every retailer chain available in the metro area of that trip and every online retailer option in the data. This is done by using the prices paid for the same UPCs in the bundle by other consumers in other stores. In that way, a mean price is calculated for every UPC at all the retailers where that product is available. Then, for each bundle purchased, the mean prices are used to compute the alternative bundle cost at every retailer. The universe of retailers in the data is the set of retailers that were visited at least once by a Nielsen panelist in the 2015-2017 period. For each trip, alternative retailers will be the two closest retailers and the two retailers with most similar cost, resulting in a total of 4 inequalities per observation. Although these moments recover θ without dealing with the computation of future values, they do not identify fixed and sunk costs as those parameters are differenced out in relation (2.9). For this reason, I discuss next how I use a second set of revealed preference relations to estimate these costs.

Identification of Subscription Costs

In order to recover fixed and sunk costs, I present a second set of revealed preference relations relative to the subscription choice. Further, I show how to use rationality constraints on future switching behavior to impose bounds on differential continuation values to evaluate the set of moment inequalities resulting from the revealed preference relations presented next.

Define the choice specific value function, conditional on s':

$$v(s, s', \epsilon) = u_{s'}(\epsilon) - c_{ss'} + \beta\mathbb{E}[V(s', \epsilon')|s']. \tag{2.12}$$

By optimality, if the consumer chooses s' conditionally on state s:

[6]See Hansen and Singleton (1982) for details on the instrumentation in rational expectation models using sample counterparts to the population orthogonality conditions.

$$\mathbb{E}[v(s,s',\epsilon)|I] \geq \mathbb{E}[v(s,\tilde{s},\epsilon)|I], \quad \forall \quad \tilde{s} \in S. \tag{2.13}$$

Joining the last two inequalities yields:

$$\begin{aligned}
\mathbb{E}[u_{s'}(\epsilon) - c_{ss'} + \beta\mathbb{E}[V(s',\epsilon')|s'] \quad |I] \quad &\geq \quad \mathbb{E}[u_{\tilde{s}'}(\epsilon) - c_{s\tilde{s}} + \beta\mathbb{E}[V(\tilde{s},\epsilon')|\tilde{s}] \quad |I], \\
&\Leftrightarrow \\
\mathbb{E}[\Delta u_{b,jk} - c_{ss'} + c_{s\tilde{s}} + \beta(\mathbb{E}[V(s',\epsilon')|s'] - \mathbb{E}[V(\tilde{s},\epsilon')|\tilde{s}] \quad |I]) \qquad &\geq \qquad 0, \quad \forall k \in J_{\tilde{s}}. \qquad (2.14)
\end{aligned}$$

Under the standard assumption that the random utility component is $i.i.d$ over time, we get:

$$\mathbb{E}\Delta V_{s'\tilde{s}'} = \Delta\mathbb{E}V_{s'\tilde{s}'} \equiv \mathbb{E}[V(s',\epsilon')] - \mathbb{E}[V(\tilde{s}',\epsilon')]. \tag{2.15}$$

The inequality (2.14) should then hold conditionally on the bundle and retailer (j) chosen by i, similarly to (2.9). It then yields:

$$\mathbb{E}[\Delta u_{b,jk} - c_{ss'} + c_{s\tilde{s}} + \beta\mathbb{E}\Delta V_{s'\tilde{s}}|I] \qquad \geq \qquad 0, \quad \forall k \in J_{\tilde{s}}. \tag{2.16}$$

Using (2.10), the inequality above is measured as:

$$\begin{aligned}
(-1+\alpha Y)\Delta\tilde{P}_{bjk} + \Delta\tilde{X}_{jk}(\beta_0 + \tilde{Z}_1\beta_1) + \Delta\tilde{T}_{jk}(\gamma_0 + \tilde{Z}_2\gamma_1 + \eta) \\
-F_{s'} - c_{ss'} + F_{\tilde{s}'} + c_{s\tilde{s}'} + \beta\mathbb{E}\Delta\tilde{V}_{s'\tilde{s}'} \qquad \geq \qquad 0, \quad \forall k \in J_{\tilde{s}'}. \qquad (2.17)
\end{aligned}$$

In order to compute this second set of moments for a candidate $\{\hat{\theta}, \hat{F}, \hat{c}\}$, we need to compute the term $\mathbb{E}\Delta\tilde{V}_{s'\tilde{s}'}$. So, I use rational switching conditions to impose bounds on these value differences. The estimation proceeds in two steps. I first estimate the utility parameters (θ) using solely the first set of moments, following Pakes et al. (2015) and Katz (2007). Secondly, I use these estimated parameters and rationality constraints to compute the differences in continuation value across alternatives. Details of the procedure to bound differential future values and estimate switching costs in presented in the Appendix. The second set of moments is then evaluated to estimate switching costs. Chapter (3) presents demand estimation results.

Next, I present the entry game played by *Big Tech* and *Grocer Partner*. For the purpose of the entry game, the demand model is used to generate a law of motion of subscribers - the state variable for firms governing the evolution of revenues. Details on how I use the demand model to build the law of motion of subscribers are presented in the second part of next chapter. Using the game setup presented next, I estimate they key parameters of firm costs to conduct counterfactuals relying on dynamics induced by both consumer lock-in (demand) and cost structure.

Chapter 3

The Entry Game: How Grocery Delivery Platforms Compete

3.1 Introduction

The online grocery market has grown significantly over the last five years as large brick-and-mortar retailers such as Walmart and Target have made large investments, and new digital platforms such as *Instacart, Google Express, Prime Now* and *Amazon Fresh* have engaged in significant entry across the United States. In June 2017, a major online retailer already engaged in online grocery operations acquired a national grocery chain. This firm's increased distribution capabilities posed an important threat to rivals contemplating online grocery investment[1]. Moreover, the merger gave the online retailer immediate access to many potential customers. On the one hand, as online delivery services rely on subscriptions and may be subject to switching costs, this generates concerns about future exertion of market power[2]. On the other hand, costs to deliver grocery products increase with distance which constrains the effects of this firm's scale across markets and makes the firm's dominance contestable by rivals. In this case, the strategic response by competitors to the acquisition can be important for the overall welfare impact on consumers.

First, this paper provides a framework to study how grocery delivery platforms such as *Amazon Prime Now* and *Instacart* make strategic entry decisions considering both the incentive to lock in consumers with subscriptions before their rival and costs of operating in different geographical markets. I study the entry timing decisions of two large platforms with differences in business models affecting their costs and entry strategies. Due

[1]See Scott-Morton et al. (2019) for a more general outline of entry barriers associated with digital platforms.

[2]For more considerations about market power in similar contexts see Zingales and Lancieri (2019) and Khan (2017)

to the proprietary nature of the data, I refer to the firms studied by names that allude to their business models: *Big Tech* is the large online retailer and its main delivery platform competitor is *Grocer Partner*. Both firms have very large population coverage across the United States and have grown significantly over the last five years. *Grocer Partner* sources products from local grocery store partners which allows it to enter markets faster than *Big Tech*, who builds new fulfillment centers dedicated to grocery delivery in each market. Both firms chase a first-mover advantage as a result of consumer switching costs associated with subscriptions. So, even though *Grocer Partner* can enter markets faster, *Big Tech*'s investments in distribution facilities can pay off in the future if the firm grows its customer base enough to benefit from returns to scale in each market.

The second goal of this paper is to evaluate the welfare impact of mergers when entry timing is crucial to competition. I evaluate to types of mergers which have opposite effects on consumer welfare. The first is an actual merger which took place in 2017 between *Big Tech* and a national grocery chain. I show that an important aspect of the welfare impact of this acquisition was *Grocer Partner*'s strategic entry response. When met with the competitive threat presented by the merger, *Grocer Partner*'s own intent to build a loyal customer base increases this firm's incentive to chase a first-mover advantage by entering new geographical markets earlier. Moreover, because competition in the grocery market is limited by geographical proximity, *Big Tech*'s increased scale provided by the acquisition had limited effects on the rival's ability to compete, contributing to the rival's response. Conversely, a potential horizontal merger between *Big Tech* and *Grocer Partner* would result in a slowdown of entry. The merged firm would not have an incentive to serve markets early due to the lack of competitive threat. I use these mergers to show the welfare effect of competition in the timing of entry in a market where firms chase a first-mover advantage.

I study firms' strategic entry timing decisions in the face of switching costs. The model is a dynamic entry game and shares many similarities with store location and entry models, such as Arcidiacono et al. (2016) and Holmes (2011). In particular, there are similarities with models of strategic spatial preemption such as Zheng (2016) and Igami and Yang (2016), where the timing of access to a particular market determines firm payoffs. However, in such models, once a location is captured by one player, it is removed from the rival's choice set. In my setting, not only firms can serve the same areas as their competitor, but customers can switch between them over time. Since switching can be costly to consumers, the second firm to enter a market will accumulate customers less quickly. Firms then compete in continuous time across independent markets and receive random opportunities to make entry decisions, such as in Arcidiacono et al. (2016). I introduce two important features to the model which allow me to study the role of the incentive to build a customer base to firms' entry decisions.

I use the estimated demand model to construct the law of motion of firm revenues using consumers' conditional choice probability of switching between subscription services over time. I also allow firms' entry cost to vary over time and estimate the rate of change using the entry model to rationalize the firms' increase in entry frequency over time. This feature, present in models of technology adoption such as Schmidt-Dengler (2006), captures the platforms' entry timing trade-off between first-mover advantage and costs.

I use this empirical framework to conduct a retrospective analysis of the recent acquisition between *Big Tech* and the national grocery chain. I find that the acquisition significantly increased both firms' speed of entry across new markets, giving consumers earlier access to the services and generating important welfare gains in the short run. Specifically, had the acquisition not happened, both firms would have entered new markets over two years later, on average. The combined costs associated with the two firms' earlier entry due to the acquisition amount to a loss of $624 M in producer surplus. However, consumer benefits across markets that were served earlier due to this merger are larger, representing a total welfare gain of $846 M. Additionally, the fact that this merger allowed the large online retailer to enter multiple markets earlier provides an explanation for the premium paid for the acquisition[3]. Moreover, until this merger occurred, this retail chain was *Grocer Partner*'s largest affiliated retailer, giving it access to approximately 23 million consumers[4]. This supports the fact that *Grocer Partner* anticipated how the acquisition would affect its ability to serve certain markets and reacted through earlier entry.

I perform a second counterfactual that simulates a potential horizontal merger between *Big Tech* and *Grocer Partner* resulting in a monopoly. I find that, due to the lack of significant competitive threat, the monopolist would not have an incentive to serve markets early. I also show that consumer losses due to delayed entry by the monopolist are larger than cost savings from this merger. In both analysis, the focus is on entry timing and firms do not choose prices in the model. For this reason, this paper is limited in its ability to capture possible future harm to consumers through prices. However, I use the demand model to show how consumers' substitution patterns as response to price changes and I find evidence that competition is important. Even though switching costs contribute to the firms' ability to raise prices, this ability is significantly reduced when consumers have more than one service alternative.

This paper relates to the literature measuring the importance of entry timing to firm decisions. In my setting, the source of early entry incentives is explicitly present in the demand model. I model the mechanism driving consumers' inertia and its relationship with firms' strategic behavior.

[3]https://mercercapital.com/financialreportingblog/amazon-whole-foods-and-value-implications/

[4]Combined population of the zip codes that had access to delivery from these stores.

3.2 Entry Game

I observe both firms' entry decisions at the time they announce the service is launching in a new location. The time between decisions are then not fixed (e.g. annual or quarterly) and decisions are observed in continuous time. Moreover, features of both firms' distribution costs and revenues suggest that markets are independent. Indeed, *Big Tech*'s operation of same-day grocery delivery is done through a separate online platform created for this purpose. The fulfillment centers used for this service are also separate from its other online retail operations. Each market gets a dedicated hub built exclusively for this type of delivery. This makes sense given that grocery and fast delivery require products to be shipped locally, unlike other product categories. For *Grocer Partner*, deliveries are fulfilled from local partner stores. Even though the platform partners with chains that have national presence, the decision of which stores are used has only local implications and restrictions. These features motivate the choice of the model that follows.

Two firms $i \in \{B, G\}$ make strategic entry decisions within each independent market $m \in \{1, 2, ..., M\}$. Time is continuous and two independent Poisson processes with parameter $\lambda_i, \quad i \in \{B, G\}$, govern decision opportunities for each firm in a market. When facing an entry opportunity, the firm observes an exogenous state $B_i \in \{0, 1\}^M$ which indicates in which market the firm can choose to make an entry decision. The firm also observes the distribution of subscribers in the market which indicates whether their rival is present and how many customers have already been locked-in: N_m.

For each move arrival in m, the *Big Tech* firm (B) can choose to enter ($j = 1$) if it wasn't already serving m and makes no further choices otherwise. Ie, the firm chooses $j \in \{0, 1\}$ if $N_{Bm} = 0$. Given a chance to move, the *Grocer Partner* (G) firm can choose to enter ($j = 1$) if it wasn't already serving the market ($N_{Gm} = 0$) and expand coverage ($j = 2$) if it already had market presence ($N_{Gm} > 0$). Neither firm can exit markets served. The stock of subscribers N_{im} in each market determines the firms' flow revenues:

$$R_i(N_m) = \bar{r}_i N_{im}, \quad i = B, G, \tag{3.1}$$

Where $\bar{r}_i$ is i's average revenue per customer, including subscription fees and consumers' purchase expenditures. When B enters market m, it needs to build a fulfillment center (FC). The size of the FC can differ across markets and is a measure of the firm's scale in each location: F_{Bm}. Operating a larger FC can imply larger fixed costs and the firm's flow profit parameter β_{B1} captures this effect. Firm G needs partnerships in each market in order to operate and expand. This firm's number of partners in each market increases over time along with its coverage. The number of partners F_{Gm} can affect the firm's fixed and variable cost of delivery through parameters β_{G1} and β_{G2}, respectively. Finally, the market's population density affects each firm's variable costs through β_{B2} and β_{G3}. Firm B's flow profits in market m are then:

$$\pi_{Bm} = \mathbf{1}_{z_{Bm}=1}[\bar{r}_B N_{Bm} + \beta_{B0} + \beta_{B1} F_{Bm} + \beta_{B2} d_m + \beta_{B3} h]. \tag{3.2}$$

Firm G's flow profits in market m are:

$$\pi_{Gm} = \mathbf{1}_{z_{Gm}>0}[(\bar{r}_G - \beta_{G2} F_{Gm}) N_{Gm} + \beta_{G0} + \beta_{G1} F_{Gm} + \beta_{G3} d_m + \beta_{G4} h], \tag{3.3}$$

Where h is an unobserved market state. Each firm also pays a sunk cost to enter which I allow to vary over time to capture firms' ability to expand at lower costs after entering many markets and to rationalize the increase in the frequency of entry for both firms observed in the data. Choice-specific sunk payoffs for B are then:

$$\psi_B = \begin{cases} \kappa_{B0} + \kappa_{B1} h + \kappa_{B2} t, & if \quad j = 1 \quad \& \quad N_{Bm} = 0, \\ 0 & otherwise. \end{cases}$$

Firm G also pays an expansion cost which can differ from the entry cost. Entry costs for this firm are then:

$$\psi_G = \begin{cases} \kappa_{G0} + \kappa_{G1} h + \kappa_{G2} t, & if \quad j = 1 \quad \& \quad N_{Gm} = 0, \\ \eta_{G0} + \eta_{G1} h + \eta_{G2} t, & if \quad j = 1 \quad \& \quad N_{Gm} > 0, \\ 0 & otherwise. \end{cases}$$

Law of Motion of Subscribers

The inequalities from the demand model imply subscription decisions for each consumer given a bundle choice. Evaluating these decisions for each of the three possible service availability cases (B alone, G alone and both B and G in the market) for a sample of consumers generates frequencies of subscription choices, conditional on each state. These frequencies are estimates for transition probabilities that represent the law of motion of subscribers in a market for each service availability case. Let m be a market where consumers have characteristics X_m. The transition matrix $M(X_m)$ describes the aggregate transition across subscription states of consumers in m. N_m describes distribution of subscribers in m across $\{0, B, G\}$. Hence, the stock of subscribers evolves according to:

$$\dot{N}_m \quad = \quad M(X_m) N_m. \tag{3.4}$$

The transition will depend on which services are available in m. Therefore, I define the following cases:

$$M(X_m) = \begin{cases} M_B(X_m), & if \quad z_{Gm} = 0 \\ M_G(X_m), & if \quad z_{Bm} = 0 \\ M_{BG}(X_m), & if \quad z_{im} > 0, \forall i \\ \quad I_3, & otherwise. \end{cases}$$

Where z_{im}, $i = \{B, G\}$ is an indicator equal to 1 if firm i's service is available in m. N_{im} for each firm is independent of characteristics of any other market. Firm costs in each market are independent of distribution centers and retail partners in other locations. Indeed, availability of both services is determined by the consumer's zip code and is highly correlated with the distance to the local FC (for B) and closest partner stores (for G). Consequently, assuming that markets are separable and firm entry decisions are made at the market level is appropriate. This implies that the exogenous state determining in which market the firm can make an entry decision, given an opportunity to move, can be expressed at the market level: B_{im}. Following the value function formulation in Arcidiacono et al. (2016), each firm's problem for a specific market is expressed as:

$$V_{ik} = \frac{\pi_{ik} + \lambda_{-i} \sum_{j \in \{0,1\}} q_{-i} \sigma_{-ijk} V_{i,\ell(-i,j,k)} + \lambda_i q_i \mathbb{E}\{V_{i,\ell(i,j,k)} + \psi_{ijk} + \epsilon_{ijk}\}}{\rho + +q_{-i} \lambda_{-i} \sigma_{-ijk} + q_i \lambda_i}, \tag{3.5}$$

Where q_i is the probability that $B_{im} = 1$. Section (3.3-3.3.2) presents the estimation steps and profit estimation results.

3.3 Results

3.3.1 Demand Estimation Results and Substitution Patterns

The estimates for the revealed preference model are presented in tables (B.34) to (B.36). The first table shows the results for the parameters where I interact each firm fixed-effect with household characteristics. All parameter estimates are in dollars per shopping trip and, the estimates of the interactions between demographic variables and each firm's fixed-effect can be directly interpreted as differences in consumer surplus after normalizing by the cost elasticity for that group[5].

The parameter results show the different channels through which consumers benefit form

[5]The value associated with a given coefficient γ is: $CS_\gamma = \frac{\gamma}{1-\alpha_1 * 10{,}000/hh\_income}$

these online retail alternatives. An important dimension for benefits generated for consumers is the distance to offline alternatives and variety of offline alternatives in the consumer's vicinity. The travel cost is one channel that affects this value: the more distant the consumer is to brick-and-mortar retailers, the higher their cost to choose an offline retailer and the more attractive is the online service. With a travel cost of \$0.55/ mile and an average distance traveled to a grocery store of 7.97 miles, consumers incur on average an utility loss due to travel costs of approximately \$4.38 per shopping trip. The variety of alternatives within 1 and 5 miles also affects the benefits that consumers get from the online services. An additional retailer within 1 mile makes *Big Tech* and *Grocer Partner* less valuable by \$0.36 and \$0.44, respectively. Between 1 and 5 miles the effect for *Big Tech*'s service is much smaller (a negative effect of \$0.04) and, the effect for *Grocer Partner*'s service is positive: an additional retailer between 1 and 5 miles increases the value of this service by \$0.26 per shopping trip. This is due to the fact that this service requires local stores to operate and, the more stores are located closely to a zip code the more partnerships *Grocer Partner* will offer and the more value this service will generate to consumers.

In order to disentangle the effect from *Grocer Partner*'s increased quality due to proximity to partner stores and the substitution effect of offering the service in an area that already has a variety of brick-and-mortar options, in column (2) I add the number of partners offered by *Grocer Partner* and the distance between the consumer and the closest store. New online services are more valuable to consumers who live further from the closest store (grocery, drug store or discount store). In the specification with ν_2, I find that *Big Tech* and *Grocer Partner*'s services are \$0.46 and \$0.34 more valuable per shopping trip, respectively, per mile of distance between the consumer and the closest store. An additional partnership offered to the consumer makes the *Grocer Partner*'s service worth \$1.44 more per shopping trip. This specification allows me to calculate the value associated with this complementarity between this service and its partners and discuss how it affects consumers differently due to their geographic living location. Zip codes with an average income of up to $45K$ that are served by *Grocer Partner* have on average 7.21 partners offering delivery whereas zip codes with average income of more than $70K$ have 10.96. This is a difference of 34% on the quality of *Grocer Partner* across these two income groups due to differences in pre-existing availability of offline retail. Low income households then miss out on approximately \$5.25 per shopping trip of welfare relative to high income households due to complementarity between *Grocer Partner* and the nearby offline retailers. Since users of delivery services make approximately 10.21 purchases per year, low income households could benefit over \$50/year more from *Grocer Partner* if they lived in zip codes with an average income of more than $70K$. On the other hand, since low income households live at a further distance from stores they benefit more form online services through the substitution channel. On average, a low income zip code in the sample is on average 6.88 miles from the closest store whereas a a high income one is at 5.44 miles. Since each mile contributes \$0.34 per trip to the value of *Grocer Partner*'s service and \$0.49 to the value to of *Big Tech*, low income households can benefit up to 26.4% more per purchase from these services through this channel. An average low income zip code then benefits approximately up to \$21.52 per year from having access to a delivery service exclusively due to distance to brick-and-mortar stores.

Other demographic characteristics that matter for welfare are age and gender (table (B.34)). Households where either the female or the male head are under 30 years old value online delivery between \$1.66 and \$3.09 more than households where one of the heads is older (depending on the service and the specification). Households of single females also value the services slightly more than other types of family: up to \$0.54 more for *Big Tech* and up to \$0.79 for *Grocer Partner* per shopping trip.

I conduct a counterfactual to measure how responsive consumers are to a change in the value of each subscription. The goal is to measure how much, in the presence of subscription lock-in, firms can raise prices in the long run. I compute these subscription elasticities for each service in two scenarios: when the consumer can choose to switch to the competitor and when there is no competition. I conduct a counterfactual where I decrease the subscription value by $-\$20$ simulating an increase in the subscription fee by the same amount or an equivalent change in prices of goods sold through each platform. I find that consumers have a similar response to such a change in the value of the *Big Tech* subscription compared to *Grocer Partner* in the case where both alternatives are available. In this case, 50% of subscribers would switch from *Big Tech* to *Grocer Partner* if *Big Tech* had a price increase of this magnitude. 46% would switch from *Grocer Partner* to *Big Tech* if *Grocer Partner* were the firm increasing prices. In the absence of the rival, switching patterns are very similar for *Grocer Partner* but quite different for *Big Tech*. When the rival is not available to the consumer, only 36% of subscribers would switch away from *Big Tech*'s service whereas 45% would switch away from *Grocer Partner*. This shows that the latter is a much closer substitute to other available alternatives such as brick-and-mortar grocers. This makes sense, given that this firm offers delivery from stores that are located close to the consumer. An important implication of these results is that, having another platform competing with *Big Tech* is important for keeping prices low in the long run.

3.3.2 Estimation of Profit Parameters and Results

The estimation takes place in two steps. First, I estimate reduced-form entry hazards for each firm using a logit with parameters varying by firm:

$$\tilde{\sigma}_{ij}(k, z, \alpha) = \frac{exp(\phi_j(k, z, \alpha))}{\sum_{j' \in \mathcal{A}_{ik}} exp(\phi'(k, z, \alpha))}, \tag{3.6}$$

Where $\phi(k, z, \alpha)$ is a linear function of state variables and z the market's unobserved state. The specification estimated is:

$$\phi^i(k, z, \alpha) = \alpha_1^i + \alpha_2^i * pop_m + \alpha_3^i * pop_m^2 + \alpha_4^i * income_m + \alpha_5^i * t + \alpha_6^i * F_{Gm} + \alpha_7^i * N_{-im}.$$

Let $h(\alpha) = (\lambda_B \sigma_B(k, z, \alpha), \lambda_G \sigma_G(k, z, \alpha)))$ be the choice hazards. In a second step, the profit structural parameters (θ) are estimated. The value function is expressed as a function of the structural parameters and the first-stage hazards $h(\hat{\alpha})$. The hazards are used to solve for the value function using *Proposition 4* in Arcidiacono et al. (2016) and generate structural hazards $\Lambda(\theta, \hat{h})$. The second-step pseudo-likelihood then uses the structural hazards to estimate $\hat{\theta}$ using Maximum Likelihood.

Tables (B.38) and (B.39) show the estimates for the firms' profit parameters. The first important difference between firms is captured by entry costs. Entry cost at time 0 for *Big Tech* is approximately the equivalent to 1 year of the average market's variable profits. The entry cost at time 0 for *Grocer Partner* is only 8% of the average market's yearly variable profits for this firm. This explains why *Grocer Partner* enters faster across markets and its pattern of entering markets by steps with progressive expansions across pockets of zip codes. Another key difference in cost structures captured by model parameters is in scale economies and the importance of population density to lower unit distribution costs. Whereas *Big Tech* has large fixed costs which increase with the size of its distribution center in a particular market, *Grocer Partner* does not. Fixed costs for the latter are estimated using the number of partnerships by market, which estimates show have more important effect on revenues than costs. On the other hand, *Big Tech*'s distribution costs fall with population density at a much faster pace than *Grocer Partner*'s. This is consistent with the fact that *Big Tech* basically stopped expanding across new markets using same-day grocery fulfillment centers after entering the largest (and densest) markets in the U.S and after acquiring stores that could be used as distribution hubs instead. Figure (B.13) shows the growth in population coverage of the two firms and *Big Tech*'s shift towards expansion with stores after the acquisition. Conversely, *Grocer Partner* continues to expand across smaller and sparser markets. Figure (B.14) shows the decrease in average market size (population) covered by *Grocer Partner*.

3.4 Counterfactuals

The first counterfactual exercise measures the importance of early entry to firms' entry decisions. I use an approach similar to Schmidt-Dengler (2006)'s to measure preemption. I compute a Nash Equilibrium where firms pre-commit to their entry times, removing the incentive to for early entry[6]. Each firm then chooses entry strategies consistent with the belief that their rival commits to the pre-commitment equilibrium. Table (B.40) shows the average time in years since the beginning of the game (June 2012) it takes each firm to enter markets in the sample. Entry decisions generated by the model with early entry incentives are such that *Big Tech* enters markets on average after 3.55 years and *Grocer Partner* after 3.97, considering expansion decisions. In the counterfactual with commitment, it takes *Big Tech* on average 4.68 years to enter a market and 5.20 years for *Grocer Partner*. Entering earlier means higher entry costs but potentially higher variable flow profits due to subscriber accumulation and rival deterrence. I compute payoffs for each firm in each equilibrium across markets to measure producer surplus losses due to early entry. Losses for *Grocer Partner* are the highest, amounting to 31.34% of its average payoff. As shown in table B.39, this firm's entry cost decrease over time at a much faster rate than *Big Tech*'s. This effect is identified by the increasing rate with which the firms enter markets over time. And it drives high relative losses of early entry for this firm. Early entry also implies important losses for *Big Tech*. On average, this firm gives up 10.84% of its payoff in each market due to early entry - table (B.41).

The second exercise measures the effects of a merger between *Big Tech* and a grocery chain. The acquisition allows the firm to enter markets faster because the stores bought can be immediately used in the grocery delivery operation. This allows the firm to partially forgo during the period following the acquisition (2018-2019) the entry cost that exists in the model. The entry timing for the post-merger period is observed in the data for two years. I compare these observed decisions with the timing predicted by the estimated pre-acquisition model for those markets (out of sample). In the model, the firm pays a high entry cost (table B.39) to enter these new markets. In particular, for *Big Tech*, entry costs are as high as one year of variable profits. With the acquisition, this firm can enter faster by reducing these costs in each market thanks to the use of stores already in place. This explains the faster rate with which it expands during the period following the merger seen in figures (B.15) and (B.13). Comparing the model with the data, I find that the firm gains on average 2.51 years in speed of entry across new markets, as shown in table (B.42). The result is similar for the competitor, who enters 2.41 years faster as a result. The rationale for the faster entry of

[6] This approach yields very similar results to one where switching costs are removed and consumers' transition (and revenues) is as table (B.37) on the right.

Grocer Partner in the data compared to the model is that the merger raised the stakes on entry for this firm as well. The firm responds to the rival's faster entry potential due to the acquisition by accelerating its own entry decisions to take advantage of consumer lock-in. Table (B.43) shows the effect of this merger on consumer welfare and how much the earlier entry induced by it represents in terms of producer surplus. Consumers gain a total of $846 in welfare over the time period in which they get earlier access to the new services as a result of this acquisition. This represents the effect of competition in entry timing on consumer welfare. This number surpasses the losses to firms due to the accelerated entry. I find that the earlier entry induced by the acquisition costs $624 to the two platforms. I compute this using *Big tech*'s pre-acquisition cost structure to infer the value of this acquisition for this firm in terms of entry timing as well as the cost it imposes on the competitor, providing a measure that rationalizes the high price paid for the grocery chain.

The third exercise analyses the consequences of a merger between *Big Tech* and *Grocer Partner*. The merged firm is a monopolist whose base of subscribers ($\tilde{N}_M$) is the sum of subscribers to both services: $\tilde{N}_M = N_B + N_G$. Due to the absence of competition, choice hazards do not include the other firm's customer base accumulated in the market. In each market, the monopolist's cost is the minimum between making use of the FC network or the set of partners. In other words, the monopolist chooses the business model in each market that yields the highest payoff. In a more sophisticated setup, the monopolist's business model could be hybrid and the firm would be able to choose what version of the service to offer to different zip codes. This is probably relevant for consumer welfare if the value of each service differs across locations in the same market. I focus for now on the entry timing effect which shouldn't be affected by the possibility of a hybrid business model. Results for this counterfactual are presented in table (B.44). The results show that, in the absence of the threat from a competitor to generate a barrier to future entry through lock-in, the firm does not have an incentive to enter markets earlier. This shows the role of competition in promoting entry of new products across markets. Indeed, I find that consumers would lose $ 2.04 Billion in welfare across the geographical markets that eventually were served exclusively due to delayed entry by the monopolist. That does not include the effects of possible future price increases by the monopolist. Indeed, as discussed in the demand results section, the *Big Tech* service is not a close substitute to existing alternatives. Consequently, in the markets where the monopolist chooses this cost structure there would be an incentive to increase prices in the future as consumers as less likely to unsubscribe as a response to a price increase. Finally, table (B.44) also shows the proportion of markets where the monopolist would choose each business model. *Big Tech* makes use of large fixed costs and has also larger economies of density, as its distribution cost is more strongly reduced with population density. In only approximately 20% of markets served this would be the most efficient cost structure. In the other 80%, *Grocer Partner*'s model of decentralized distribution is the most profitable choice.

Conclusion

This dissertation provides an empirical framework to study the relationship between strategic entry timing and consumer welfare in a setting where consumer lock-in is a driving force of entry. I study the entry timing decisions of two firms with distinct business models. Differences between business models allow me to distinguish entry incentives driven by cost structure from consumer lock-in. I do so by using data on two platforms offering grocery delivery in a variety of U.S. markets. The model is a useful setup for both demand a supply-related questions relevant for current antitrust policy discussions around digital platforms in markets where geography also affects costs and competition. First, I measure the importance of consumer lock-in due to switching costs associated with subscriptions, a pricing strategy widely used in e-commerce and other platform-enabled markets. Second, I model the relationship between demand dynamics and supply timing decisions in an empirically tractable way. Then, by relating these two sides, I measure the importance of the demand mechanism as well as costs to firms' entry strategies.

Results show that sunk costs associated with subscriptions generate significant inertia in platform choice. In absence of switching costs, consumers would switch ten times more often across services. This inertia in customer base makes firms' decision to enter markets time-sensitive, as entering late comes with the cost of having to breach the barrier of consumer lock-in created by the rival. On the other hand, entering early implies higher entry costs and the efficiency loss associated with this incentive is, on average, 10% of producer surplus for the firm with high fixed costs and 30% of producer surplus for the firm with high variable costs.

I use the model to evaluate the impact of two types of mergers on consumer welfare and efficiency. Each merger has very different implications for each of these outcomes, showing that timing of entry is an important dimension to be considered in merger and welfare analysis in markets being gradually created by geographical entry. The first is the acquisition of a grocery chain by *Big Tech*. This merger reduced the entry cost of a firm for which this was the main entry barrier. This allowed the firm to enter markets much quicker following the acquisition. In contrast, the rival with low entry costs responded to the acquisition by increasing the pace of its own entry decisions immediately after the acquisition announcement by *Big tech*. In the model, this is captured by the rival's expectation that *Big Tech* will establish consumer lock-in by accumulating subscribers in new markets faster than before. This then increases the payoff of early entry for *Grocer Partner*. As a consequence, many markets that would only receive one or both services over 8 years after the first platform is created get them more than 2 years earlier. Even though this merger may have other consequences that are important for competition and consumer welfare which are not within the scope of this dissertation, it fostered consumer welfare through strategic entry timing.

Conversely, a merger that establishes a monopoly in the delivery market has the opposite effect. If *Big Tech* decides to buy off *Grocer Partner*, the consequence predicted is a significant slow down in entry speed. In particular, if this merger had occurred at the beginning of the entry game, consumers would have gained access to these technologies at least 6 years later, on average. Again, this is without considering any dimension for which market structure would also be relevant for, including the incentive to create these services in the first place. Finally, this framework can be used to analyze many other markets that blend digital technology and offline cost structures that are under the antitrust scrutiny today. Indeed, timing of access to particular geographical markets is a crucial factor to a firm's decision to buy another business. And, more importantly, the way competitors are expected to react, given features of the market, is an important factor to consider when analyzing whether the acquisition is harmful to consumers of not.

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Appendix A

Appendix to Chapter 2

A.1 Appendix II - Estimation of Switching Costs

A.1.1 Deriving the System of Differential Values

In order to estimate the switching costs, I will compare the consumer's optimal subscription action to an alternative choice that could have been taken. This will generate a set of inequalities that will then be used as moments for estimation. The idea is the same as the one used to estimate the set of parameters $\hat{\theta}$ in the static portion of the utility. However, to estimate the switching costs wee need an approximation of the continuation value of each subscription action for each trip in the data. For example, I want to be able to compute:

$$\Delta u_{BG} - F_B + F_G + c_{BG} + \beta[\mathbb{E}V(B, \epsilon') - \mathbb{E}V(G, \epsilon')] \geq 0. \tag{A.1}$$

This inequality means that, if a trip t for consumer i is observed in the data such that the state in that period for i is B and the consumer chooses $S' = B$ then, the difference between the choice specific value of B and the choice specific value of G needs to satisfy the revealed preference relation (A.1). Next, I will show how to approximate $\mathbb{E}\Delta V_{BG}(\epsilon') = \mathbb{E}V(B, \epsilon') - \mathbb{E}V(G, \epsilon')$ to compute that inequality for a set of parameters using this example.

$$\begin{aligned}
\mathbb{E}\Delta V_{BG}(\epsilon') &= \mathbb{E}V(B, \epsilon') - \mathbb{E}V(G, \epsilon') \\
&= \mathbb{E}[V(B, \epsilon') - V(G, \epsilon')] \\
&= \mathbb{E}[\max\{u_B(\epsilon') - F_B + \beta\mathbb{E}V(B, \epsilon''); u_G(, \epsilon') - F_G - c_{BG} + \beta\mathbb{E}V(G, \epsilon''); u_0(\epsilon') + \beta\mathbb{E}V(0, \epsilon'')\} \\
&- \max\{u_B(\epsilon') - F_B - c_{GB} + \beta\mathbb{E}V(B, \epsilon''); u_G(\epsilon') - F_G + \beta\mathbb{E}V(G, \epsilon''); u_0(\epsilon') + \beta\mathbb{E}V(0, \epsilon'')\}] \\
&= \mathbb{E}[\max\{c_{GB}; \Delta u_{BG} - F_B + F_G + \beta\mathbb{E}\Delta V_{BG}; \Delta u_{B0} - F_B + \beta\mathbb{E}\Delta V_{B0}; \\
&\quad \Delta u_{GB} - F_G + F_B - c_{BG} + c_{GB} + \beta\mathbb{E}\Delta V_{GB}; -c_{BG}; \Delta u_{G0} - F_G - c_{BG} + \beta\mathbb{E}\Delta V_{G0}; \\
&\quad \Delta u_{0B} + F_B + c_{GB} + \beta\mathbb{E}\Delta V_{0B}; \Delta u_{0G} + F_G + \beta\mathbb{E}\Delta V_{0G}; \quad 0\},
\end{aligned} \tag{A.2}$$

Where

$$\Omega_{BB,GB} = \{\epsilon \in \Omega_\epsilon | B = argmax_{a \in S} V_a(B,\epsilon) \wedge B = argmax_{a \in S} V_a(G,\epsilon)\}.$$

Hence,

$$\begin{aligned}
\mathbb{E}\Delta V_{BG}(\epsilon') \quad = \quad & P(BB,GB)[c_{GB}] + P(BB,GG)[\mathbb{E}[\Delta u_{BG}|\Omega_{BB,GB}] - F_B + F_G + \beta\mathbb{E}\Delta V_{BG}] + \\
& P(BB,G0)[\mathbb{E}[\Delta u_{B0}|\Omega_{BB,G0}] - F_B + \beta\mathbb{E}\Delta V_{B0}] + P(BG,GB)[\mathbb{E}[\Delta u_{GB}|\Omega_{BG,GB}] - \\
& F_G + F_B - c_{BG} + c_{GB} + \beta\mathbb{E}\Delta V_{GB}] + P(BG,GG)[-c_{BG}] + P(BG,G0)[\mathbb{E}[\Delta u_{G0}|\Omega_{BG,G0}] - \\
& F_G - c_{BG} + \beta\mathbb{E}\Delta V_{G0}] + P(B0,GB)[\mathbb{E}[\Delta u_{0B}|\Omega_{B0,GB}] + F_B + c_{GB} + \beta\mathbb{E}\Delta V_{0B}] + \\
& P(B0,GG)[\mathbb{E}[\Delta u_{0G}|\Omega_{B0,GG}] + F_G + \beta\mathbb{E}\Delta V_{0G}] + P(B0,G0)[0]. \qquad (A.3)
\end{aligned}$$

Where $P(S_1a_1, S_2a_2)$ is the probability of ϵ' being in the set $\Omega_{S_1a_1,S_2a_2}$ such that, $\forall\epsilon' \in \Omega_{S_1a_1,S_2a_2}$, if state S_1, action a_1 is taken and, if state S_2 occurs, action a_2 is taken. Note that this set can differ for each consumer because u^i_S can differ across consumers, for any S. So, we are integrating over ϵ' in a way that is feasible because the number of subscription actions and states is small. Moreover, consumers' history of actions is observed in the data so that these probabilities can be approximated by frequencies in the data. But, even with a lot of data, it would be hard to observe the same consumer enough times in different states, given that most consumers never switch between subscriptions. And, we cannot observe the same shock to the consumer in different states. So, a couple of things are done to recover the probabilities above. The first one is to think about the rational implications of two pairs of actions to see if they are pairs with positive probabilities or not.

Similar expressions to equation (A.3) can be derived for $\mathbb{E}\Delta V_{B0}(\epsilon')$ and $\mathbb{E}\Delta V_{G0}(\epsilon')$, noting that $\mathbb{E}\Delta V_{BG}(\epsilon') = -\mathbb{E}\Delta V_{GB}(\epsilon')$ and $\mathbb{E}\Delta V_{B0}(\epsilon') = -\mathbb{E}\Delta V_{0B}(\epsilon')$ and so on. So, we have a system of N[1] equations and N unknowns that we can use to solve for the difference in values across states for an individual. However, this system also contains the unknown values of current expected differential utilities: $\mathbb{E}[\Delta u_{ss'}|\Omega_{ss',\tilde{s}\tilde{s}'}]$. I use rationality conditions that have to hold in each case to bound these values and solve the system.

Transition probabilities are estimated non-parametrically from frequencies in the data. For a given individual, we can calculate $Pr(S' = a|S = s)$ based on frequencies of actions conditional on the observed state. However, the probabilities needed to solve the system of differential values requires a different set of probabilities. They are, nonetheless, related. For example, the set of shocks that, for a given individual, would rationalize $S' = G|S = B$ is a subset of shocks that would rationalize $S' = B|S = B$. Hence, $Pr^i(S' = B|S = B \wedge S' = G|S = B) = Pr^i(S' = G|S = B)$. Additionally, some of these sets of shocks are empty and therefore, have probability zero.

[1] If conditional choice probabilities are determined at the individual level then, for each individual, we have $N = 3$.

A.1.2 Bounding Differential Values and Estimation

The system of differential values in (A.1.1) has two types of unknowns: expected differential utilities, conditional on a subset of values for ϵ', and unconditional expected differential value functions. These unknowns appear in pairs in the system that includes equation (A.3). For example, the difference between the value of action B when the state is B and the value of action 0 when the state is G is: $\mathbb{E}[\Delta u_{B0}|\Omega_{BB,G0}] - F_B + \beta\mathbb{E}\Delta V_{B0}$. So, the difference between the flow utility of action a_1 in state S_1 and of action a_2 in state S_2 and the difference between the future values associated with these two actions appear in pairs. This happens because the subscription choice in the current period determines the set of choices in that period and, consequently, the flow utility as well as the state in the next period. I propose a method to impose bounds on these pairs of differential utilities and values.

Suppose that when the state is s the consumer chooses s' and when the state is $\tilde{s}$ the consumer chooses $\tilde{s}'$. This means that $\epsilon \in \Omega_{ss',\tilde{s}\tilde{s}'}$ and the following have to hold:

$$\mathbb{E}[v(s,s',\epsilon) - v(\tilde{s},\tilde{s}',\epsilon)] = \mathbb{E}[\Delta u_{s'\tilde{s}'}|\Omega_{ss',\tilde{s}\tilde{s}'}] - F_{s'} + F_{\tilde{s}'} + \beta\mathbb{E}\Delta V_{s'\tilde{s}'}. \tag{A.4}$$

Then, $\forall \hat{s} \neq s' \in S$, the following holds:

$$\mathbb{E}[u_{s'}|\Omega_{ss',\tilde{s}\tilde{s}'}] - F_{s'} + \beta\mathbb{E}V(s',\epsilon') \geq \mathbb{E}[u_{\hat{s}}|\Omega_{ss',\tilde{s}\tilde{s}'}] - F_{\hat{s}} - c_{s\hat{s}} + \beta\mathbb{E}V(\hat{s},\epsilon'), \tag{A.5}$$

Including for the case where $\hat{s} = \tilde{s}'$. Therefore:

$$\Rightarrow \quad \mathbb{E}[\Delta u_{s'\tilde{s}'}|\Omega_{ss',\tilde{s}\tilde{s}'}] + \beta\mathbb{E}\Delta V_{s'\tilde{s}'} \geq F_{s'} - F_{\tilde{s}'} - c_{s\tilde{s}'}. \tag{A.6}$$

And, $\forall \hat{s} \neq \tilde{s}' \in S$, the following also holds:

$$\mathbb{E}[u_{\tilde{s}'}|\Omega_{ss',\tilde{s}\tilde{s}'}] - F_{\tilde{s}'} + \beta\mathbb{E}V(\tilde{s}',\epsilon') \geq \mathbb{E}[u_{\hat{s}}|\Omega_{ss,\tilde{s}\tilde{s}}] - F_{\hat{s}} - c_{s\hat{s}} + \beta\mathbb{E}V(\hat{s},\epsilon'), \tag{A.7}$$

Including for the case where $\hat{s} = s'$. Therefore:

$$\begin{aligned} &\Rightarrow \quad \mathbb{E}[\Delta u_{\tilde{s}'s'}|\Omega_{ss',\tilde{s}\tilde{s}'}] + \beta\mathbb{E}\Delta V_{\tilde{s}'s'} \geq F_{\tilde{s}'} - F_{s'} - c_{\tilde{s}'s} \\ &\Leftrightarrow \quad \mathbb{E}[\Delta u_{s'\tilde{s}'}|\Omega_{ss',\tilde{s}\tilde{s}'}] + \beta\mathbb{E}\Delta V_{s'\tilde{s}'} \leq F_{s'} - F_{\tilde{s}'} - c_{\tilde{s}'s}. \end{aligned} \tag{A.8}$$

Inequalities (A.8) and (A.6) then provide upper and lower bounds based on intertemporal rationality constraints for the unknown values of $\mathbb{E}[\Delta u_{s'\tilde{s}'}|\Omega_{ss',\tilde{s}\tilde{s}'}] + \beta\mathbb{E}\Delta V_{s'\tilde{s}'}$. I use these bounds to solve the system with all differential future values such as in equation (A.3). This gives estimates for each $\mathbb{E}\Delta V_{ss'}$ which can be used, given a guess for parameters, to solve the second set of moment inequalities such as equation (A.1). The estimation steps are summarized below.

1. Compute conditional choice probabilities (CCP) of transitioning between each element of $\{0, B, G\}$ between two purchase decisions. For a guess of parameters $\{(\hat{F}'_s, \hat{c}_{ss'})\}_{s,s' \in S^2}$:

2. Use the CCP and the system of equations that result from the moment inequalities to write the difference in future values recursively.

3. For each combination of differential future values - each pair (s, s'), use the intertemporal rationality constraints to create bounds for the unknown part of the utility depending only on parameters.

4. Use step 3 to solve for differential future values using the system in step 2.

5. Use differential values from step 4 to solve for set of the second set of moment inequalities and search for parameters to minimize deviations from these moments.

Appendix B

Figures and Tables

Figure B.1: Services Take-up

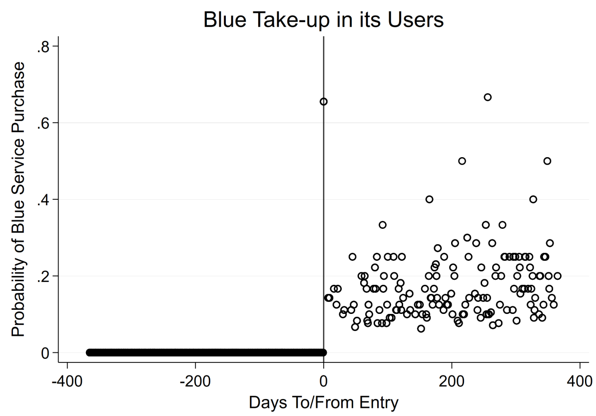


Figure B.2: Big Tech Firm Take-up

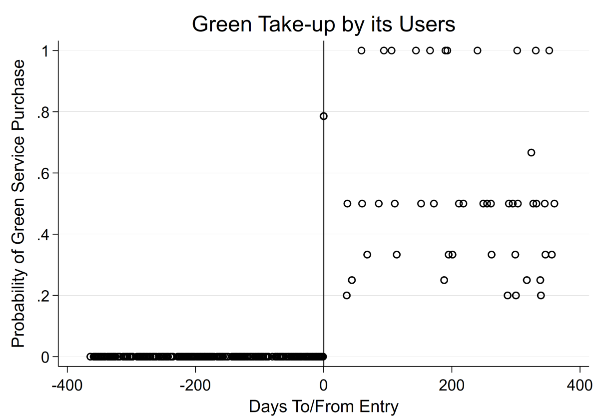


Figure B.3: Grocer Partner Firm Take-up

Note: Frequency of Big Tech or Grocer Partner service purchases by number of days from launch among all online transactions of Nielsen panelists that have used either service in the period of 2015-2016. Panelists making these transactions are spread across 27 metro areas where the launch of each service has occurred at a different date. Graphs show that the scraped arrival dates match the timing of when purchases start emerging in the Nielsen data.

Table B.1: Shopping Trips in Panel

	Grocer Partner Not Available	Grocer Partner Available	Total
Big Tech Not Available	312,158	364,593	676,751
Big Tech Available	369,491	334,907	704,398
Total	681,649	699500	1,381,149

Table B.2: Households in Panel

	Grocer Partner Not Available	Grocer Partner Available	Total
Big Tech Not Available	2,132	2,462	4,594
Big Tech Available	2,477	2,231	4,708
Total	4,609	4,693	9,302

Table B.3: Corresponding Zip Codes in Panel

	Grocer Partner Not Available	Grocer Partner Available	Total
Big Tech Not Available	355	314	669
Big Tech Available	354	326	680
Total	709	640	1349

Table B.4: Sample Zip Codes Tested

	Grocer Partner Not Available	Grocer Partner Available	Total
Big Tech Not Available	8,913	4,863	13,776
Big Tech Available	354	1,716	2,070
Total	9,267	6,579	15,846

Table B.5: Zip Codes Tested Mean Income

	Grocer Partner Not Available	Grocer Partner Available	Total
Big Tech Not Available	84,033.76	83,927.38	83,971.76
Big Tech Available	73,044.17	88,048.86	82,683.82
Total	75,308.69	87,356.78	82,918.19

Note: Table includes number of observed shopping trips to the 4 channels of interest (Grocery, Discount Store, Drug Store and Online Shopping) during 2015-2016 for panelists in the 27 metro areas where there are launches of either Big Tech or Grocer Partner (or both) in one of these two years. This includes trips before and after the launches. The total number of trips will correspond to the total number of observations in tables (B.17)-(B.19) across all three income groups. The corresponding number of households making those trips and zip codes are also presented. The last two tables contain all zip codes with information on availability status scraped from services' website. This larger sample of zip codes is used to match income data from the 2012-2016 American Community Survey 5-Year Estimates (ACS) and supplemetary information on the number of retail establishments by NAICS code come from the Zip Codes Business Patterns (ZBP) 2015.

Table B.6: Metro Areas Where Panelists Who Are Same-day Delivery Users Are Located

Metro Area	2016	2015
Atlanta	x	x
Baltimore	x	x
Boston	x	x
Chicago	x	x
Cincinnati	x	
Columbus	x	
Dallas	x	x
Denver	x	x
Houston	x	x
Indianapolis	x	x
Las Vegas	x	x
Los Angeles	x	x
Miami	x	x
Minneapolis-St. Paul	x	x
Nashville	x	
New York	x	x
Orlando	x	
Phoenix	x	x
Portland	x	x
Raleigh-Durham	x	
Richmond	x	x
Sacramento	x	
San Antonio	x	x
San Diego	x	x
San Francisco	x	x
Seattle	x	x
Tampa	x	
Washington DC	x	x

Note: Table displays metro areas associated with panelists that use either service (Big Tech or Grocer Partner) in 2015-2016.

Table B.7: Shopping Trip Characteristics By Retail Channel

Table B.8: Cost of Bundles Bought ($)

	Mean Value Spent Per Trip	Std. Dev.
Discount Store	59.20	67.22
Drug Store	29.52	48.79
Grocery	45.82	52.03
Online Shopping	68.41	97.16

Table B.9: Distances Traveled (miles)

	Min. Distance Traveled in miles	Std. Dev.
Discount Store	8.68	7.54
Drug Store	9.50	7.38
Grocery	7.97	6.75

Table B.10: Number of Product UPCs

	Average Nb. of UPCs/Retailer	Std. Dev.
Discount Store	49,694.25	32,123.79
Drug Store	7,764.16	5,098.56
Grocery	22,625.52	17,064.89
Online Shopping	1,317.12	1,220.10

Note: Each observation is a shopping trip to the relevant channels in the data during 2015-2016 in the 27 metro areas used. Table (B.8) presents the mean dollar value of the bundles purchased in trips associated with each channel. Table (B.9) presents the mean distance between panelists and the closest store of each channel. Table (B.10) presents the average number of UPC codes bought in stores owned by retailers associated with each channel.

Table B.11: Differences in Grocery Baskets Across Income Groups in Trips to Same Retailer

Income Bracket	Nb. of Fresh Produce in Basket	std. dev.
$[0, 45,000)$	1.05	.75
$[45,000 - 70,000)$	1.32	1.14
$\geq 70,000$	1.51	1.09

Table B.12: Differences in Grocery Baskets Across Income Groups in Trips to Grocer Partner Firm

Income Bracket	Nb. of Fresh Produce in Basket	Std. dev.
$[0 - 45,000)$	1.41	1.06
$[45,000 - 70,000)$	1.37	1.21
$\geq 70,000$	1.60	1.20

Note: Table (B.11) presents the average and standard deviation of the number of fresh produce items in bundles purchased by households in each income group. For each retailer visited by multiple panelists of each income group, means in table (B.11) are calculated across panelists that visit the same retailer. Table (B.12) shows means and standard deviations for the number of fresh produce in the basket purchased for panelists that use the Grocer Partner service across income groups.

Table B.13: Demographic Characteristics of Panelists

	Sample	Big Tech Users	Grocer Partner Users
Under 30 years old	39.44	44.22	55.84
Under 50 years old	63.21	55.20	72.73
Single Female	26.47	31.79	42.86
Single Male	9.96	12.14	11.69
White	81.60	84.10	70.13
Black	10.46	8.38	20.78
Asian	3.16	3.17	1.30
Other (race)	4.77	4.05	7.79
Hispanic	6.46	8.96	10.39
Children Under 18	23.90	11.85	18.18
Active Internet	94.94	97.40	97.40
Highest Degree in Household:			
Grade School	0.15	0.29	0.00
Some High School	0.98	0.16	0.00
Graduated High School	18.18	17.63	9.09
Some College	28.79	31.21	29.87
Graduated College	34.00	35.55	31.17
Post College Grad	17.90	14.16	29.87
Income < 45K	39.34	42.20	31.17
Income [45K, 70K)	24.89	27.75	32.47
Income ≥ 70K	35.77	30.06	36.36

Note: All variables are dummies. Hence, the table shows the proportion panelists with each demographic characteristic within each subgroup. The first column shows the proportions for the entire set of Nielsen panelists in 2015-2016. Single female and male households are households with no male head of household and no female head of household, respectively.

Table B.14: Number of Grocery Stores Per Capita in Zip Codes of Different Income Levels

Income Group	Zip Code Mean	Std. dev.
Income < 45K	.26	1.86
Income [45K - 70K)	.28	1.89
Income > 70K	.96	3.03

Table B.15: Number of Drug Stores in Zip Codes Per Capita of Different Income Levels

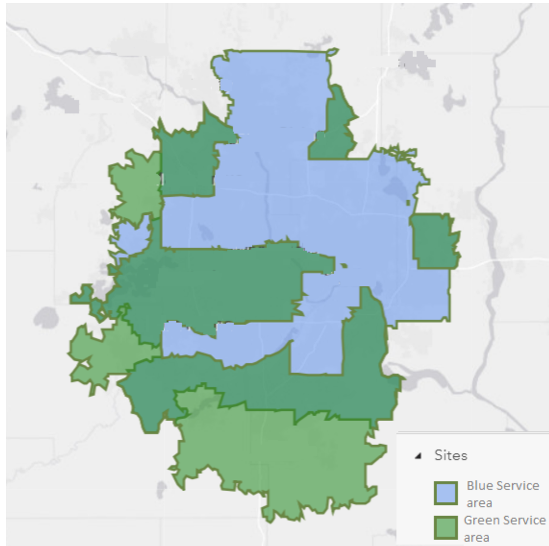
Income Group	Zip Code Mean	Std. dev.
Income < 45K	.076	.729
Income [45K - 70K)	.070	.551
Income > 70K	.376	1.471

Table B.16: Number of General Merchandise Stores Per Capita in Zip Codes of Different Income Levels

Income Group	Zip Code Mean	Std. dev.
Income < 45K	4.20	4.63
Income [45K - 70K)	3.28	3.62
Income > 70K	2.36	2.91

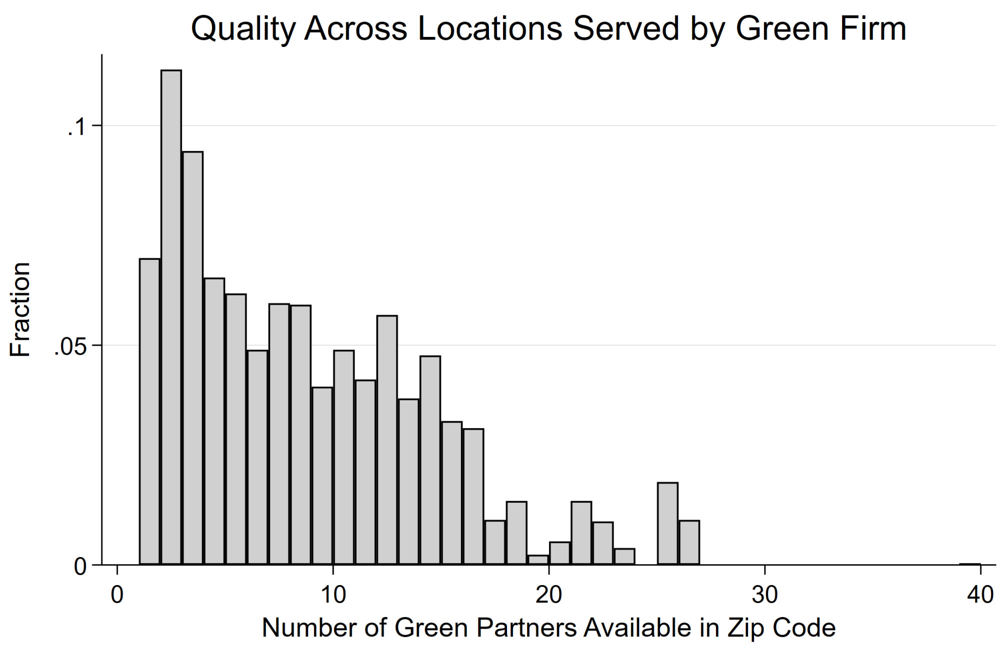
Note: Average income and population by zip code comes from the 2012-2016 American Community Survey 5-Year Estimates (ACS) and the number of retail establishments by NAICS code come from the Zip Codes Business Patterns (ZBP) 2015.

Figure B.4: Delivery Radius By Service



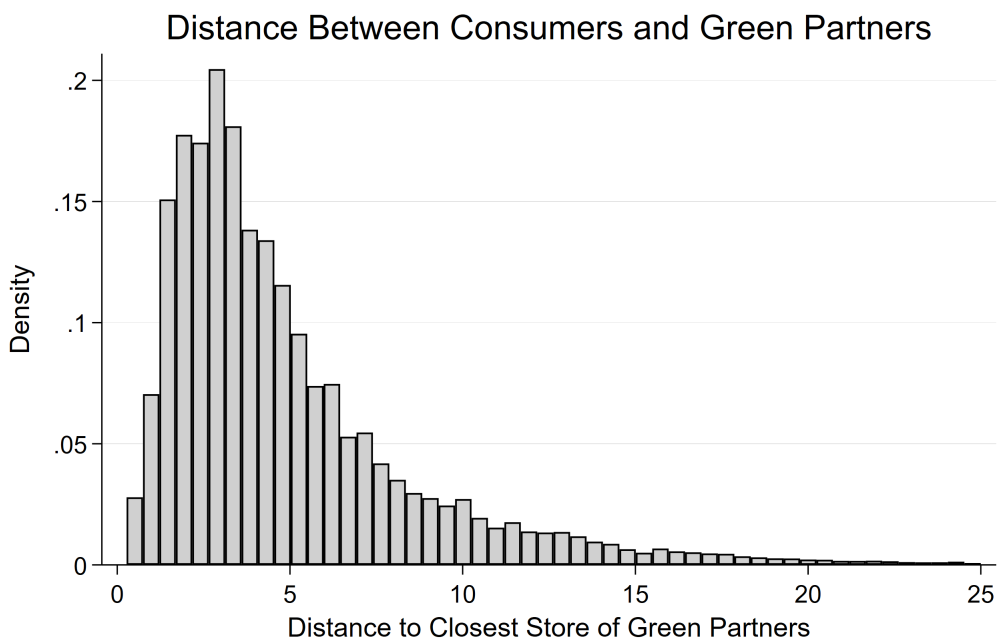
Note: Example of delivery radius for a metro area in the sample at the beginning of the sample period. Zip codes in blue are uniquely served by Big Tech firm, zip codes in light green are uniquely served by Grocer Partner firm and the dark green area corresponds to zip codes served by both services.

Figure B.5: Distribution of Partners Available on Grocer Partner Platform



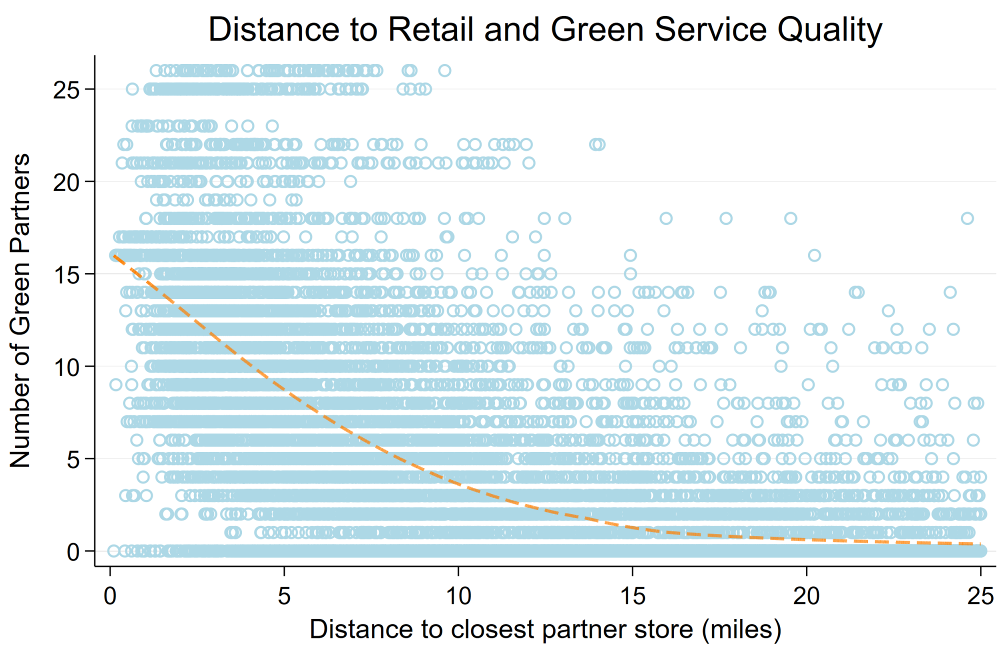
Note: An observation is a zip code and the the number of retailers that fulfill deliveries to that zip code though Grocer Partner's platform.

Figure B.6: Distribution of Minimum Distance Between Consumers and Grocer Partner Affiliated Stores



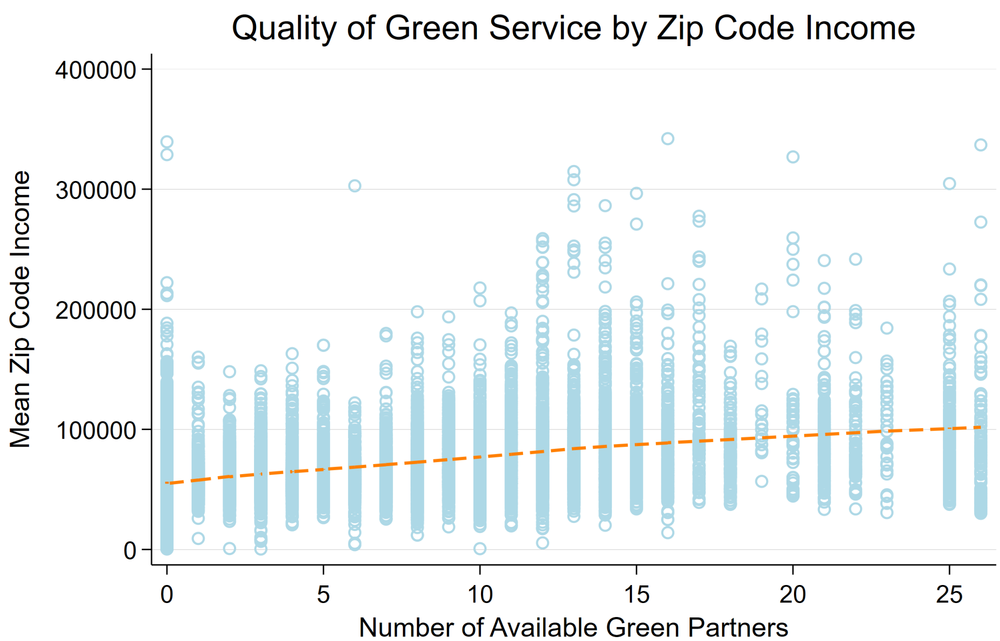
Note: An observation is a zip code served by the Grocer Partner firm and the distance from that zip code's centroid to the closest store of a retailer that is a partner of Grocer Partner firm.

Figure B.7: Distance to Stores and Number of Partners Available on Grocer Partner's Platform



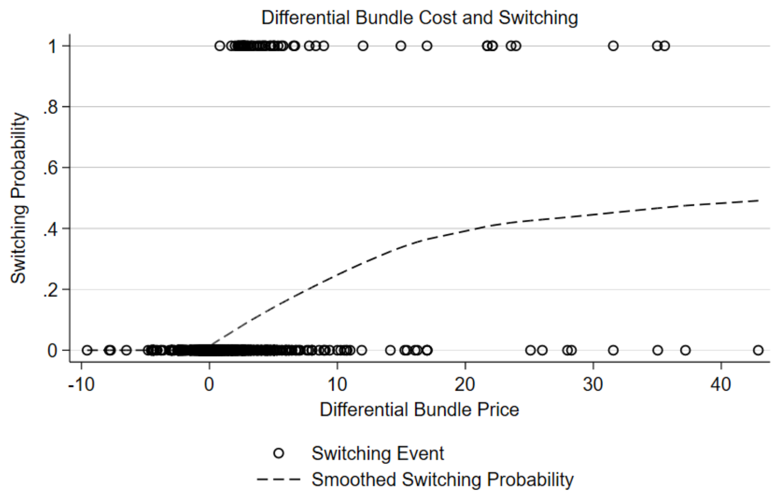
Note: An observation is a zip code served by the Grocer Partner firm, a distance from that zip code's centroid to the closest store of a retailer that is a partner of Grocer Partner firm and the number of retailers that fulfill deliveries to that zip code though Grocer Partner's platform. This graph displays the lowess regression aproximation of the relationship between distance from partner stores and number of partners available.

Figure B.8: Distance to Stores and Zip Code Income



Note: An observation is the mean income of households in each U.S. zip code and the number of partners offered by the Grocer Partner service in that zip code. The mean household income by zip code comes from the 2012-2016 American Community Survey 5-Year Estimates (ACS). This graph displays the lowess regression approximation of the relationship between the number of partners offered and the zip code mean household income.

Figure B.9: Higher Differential Prices Induce Limited Switching



Note: This graph shows how consumers' switching behavior relates to differences in prices across platforms for the bundle purchased. Each observation is a price difference of the combined products purchased compared to the other platform when the consumer has the opportunity to switch to purchase the same bundle. The smoothed predicted probability is predicts whether the consumer switched platforms, given the price difference of the bundle purchased.

Figure B.10: National Presence and Local Footprint of Same-day Grocery Delivery (2017)

Note: The map shows how Big Tech and Grocer Partner have country-wide presence. Entry decisions across markets pinned occurs during 2012-2017 and are used in entry game estimation. Each colored pin represents a different grocery delivery service. Big Tech is represented by blue squares and Grocer Partner by green pins. Yellow and red pins represent two other grocery delivery services with regional coverage presented for scale.

Figure B.11: Big Tech Coverage around Fulfillment Center

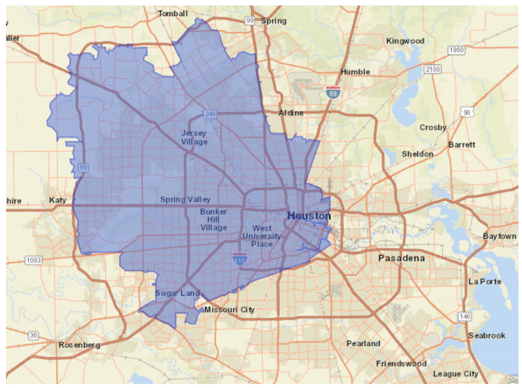
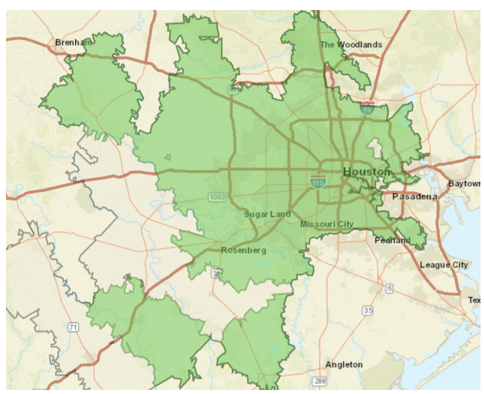


Figure B.12: Grocer Partner Scattered Coverage around Stores



Note: Each map is an example of delivery radius for a metro area (Houston) showing how Big Tech (left) has a contiguous delivery radius around its fulfillment center whereas Grocer Partner (right) has often isolated pockets around partner stores.

Figure B.13: Entry Costs and Total Population Served by Firm

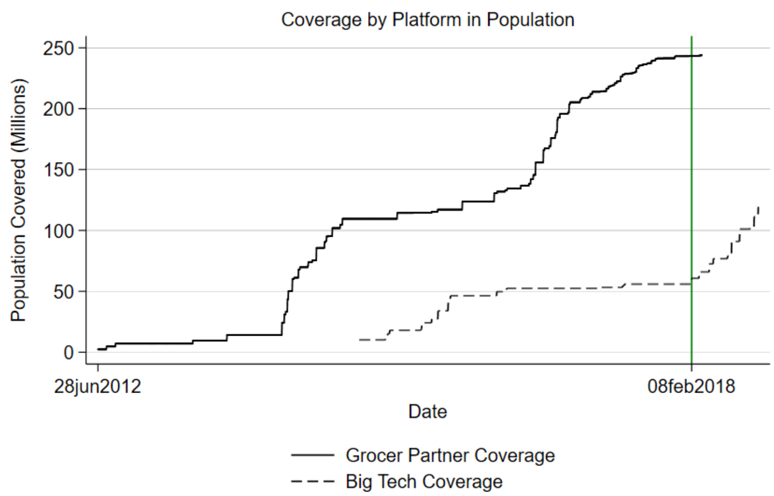
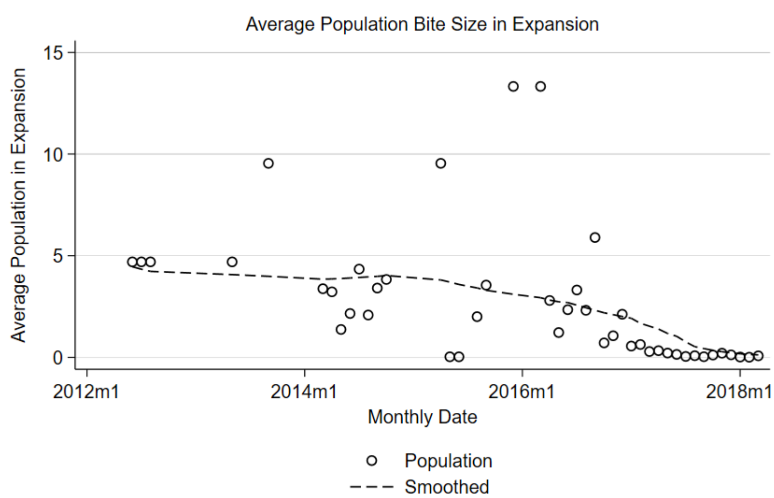
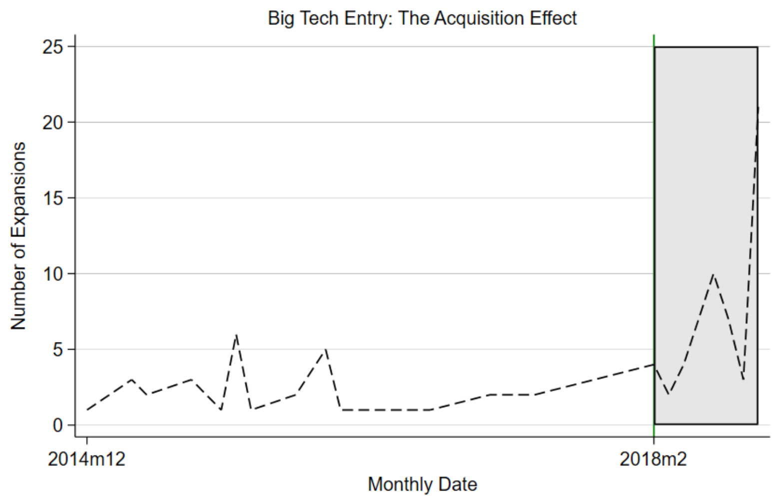


Figure B.14: With Low Entry Costs, Grocer Partner Enters Smaller Markets Over Time



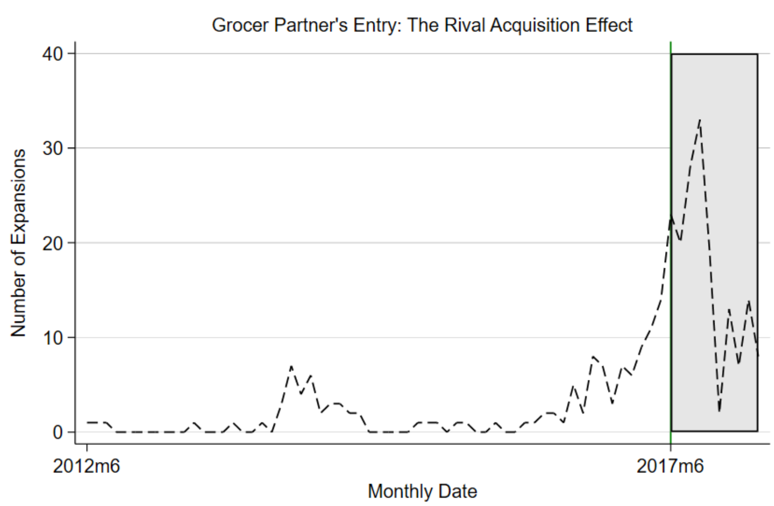
Note: The top graph shows how with low entry costs, Grocer Partner, grows its coverage faster than Big Tech. The vertical line represents the date when Big Tech announces the first entry using the brick-and-mortar grocery stores it acquires in 2017, allowing it to grow faster. The bottom graph shows the average size in population in Grocer Partner's expansions. By 2018, markets are as small as 300 thousand people, showing how this firm's cost relies little on market size.

Figure B.15: Acquisition Lowers Big Tech Entry Costs inducing Faster Entry



Note: In February 2018, Big Tech starts making use of the newly acquired grocery stores as delivery hubs. As a result, the figure shows how the firm is able to start operating in new markets faster than before. Each observation is the sum of entry decision announcements made by Big Tech in a month.

Figure B.16: The "Big Tech Effect": Grocer Partner Reacts to Acquisition with Faster Entry



Note: In June 2017, Big Tech publicly announces the acquisition of a brick-and-mortar grocery chain in Grocer Partner's network of affiliated retailers. Each observation is the sum of entry decision announcements made by Grocer Partner in a month.

Table B.17: Effect of Big Tech and Grocer Partner Service Launches on Probability of Grocery Store Purchase by Users of Each Service

	(OLS)	(OLS)	(OLS)
VARIABLES	< 45K	[45K - 70K)	> 70K
Grocer Partner Available * User	-0.106***	-0.121***	-0.330***
	(0.0177)	(0.0402)	(0.0227)
Big Tech Available * Big Tech User	-0.352***	-0.114***	-0.0271*
	(0.0310)	(0.0111)	(0.0140)
Constant	0.465***	0.535***	0.552***
	(0.0187)	(0.00710)	(0.00737)
Household FE	YES	YES	YES
Month FE	YES	YES	YES
Observations	96,475	651,726	632,948
R-squared	0.035	0.021	0.019

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Note: Observations include all trips to grocery stores, discount store and drug stores made by households in the 27 metro areas that contain Big Tech and Grocer Partner service users in 2015-2016. For each trip, the dependent variable takes value 1 if the store visited belong to the Grocery channel. Coefficients represent the change in the probability of a same-day delivery service user making a trip to a grocery store after the this new service become available in their zip code.

Table B.18: Effect of Big Tech and Grocer Partner Service Launches on Probability of Discount Store Purchase by Users of Each Service

VARIABLES	(OLS) < 45K	(OLS) [45K - 70K)	(OLS) > 70K
Grocer Partner Available * User	0.0306	0.0787**	-0.0277
	(0.0319)	(0.0342)	(0.0190)
Big Tech Available * User	-0.0759***	-0.107***	-0.106***
	(0.0253)	(0.00944)	(0.0117)
Constant	0.156***	0.158***	0.154***
	(0.0152)	(0.00603)	(0.00617)
Household FE	YES	YES	YES
Month FE	YES	YES	YES
Observations	96,475	651,726	632,948
R-squared	0.100	0.077	0.071

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Note: Observations include all trips to grocery stores, discount store and drug stores made by households in the 27 metro areas that contain Big Tech and Grocer Partner service users in 2015-2016. For each trip, the dependent variable takes value 1 if the store visited belong to the Discount Store channel. Coefficients represent the change in the probability of a same-day delivery service user making a trip to a discount store after the this new service become available in their zip code.

Table B.19: Effect of Big Tech and Grocer Partner Service Launches on Probability of Drug Store Purchase by Users of Each Service

VARIABLES	(OLS) < 45K	(OLS) [45K - 70K)	(OLS) > 70K
Grocer Partner Available * User	0.0248	0.000243	0.0239*
	(0.0235)	(0.0250)	(0.0141)
Big Tech Available * User	0.00583*	-0.0421***	-0.0173**
	(0.00352)	(0.00690)	(0.00871)
Constant	0.0970***	0.0664***	0.0609***
	(0.0126)	(0.00441)	(0.00457)
Household FE	YES	YES	YES
Month FE	YES	YES	YES
Observations	96,475	651,726	632,948
R-squared	0.081	0.066	0.057

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Note: Observations include all trips to grocery stores, discount store and drug stores made by households in the 27 metro areas that contain Big Tech and Grocer Partner service users in 2015-2016. For each trip, the dependent variable takes value 1 if the store visited belong to the Drug Store channel. Coefficients represent the change in the probability of a same-day delivery service user making a trip to a drug store after the this new service become available in their zip code.

Table B.20: Effect of Offline Retail Availability on Probability of Grocer Partner Service Usage

VARIABLES	(OLS) Grocer Partner	(OLS) Grocer Partner	(OLS) Grocer Partner
Distance to Closest Grocer Partner Affiliated Store (miles)	-0.000384	0.00215***	0.00170***
	(0.000513)	(0.000556)	(0.000556)
Number of Grocer Partner Affiliated Available		0.00334***	0.00329***
		(0.000306)	(0.000304)
Number of Stores within 1 mile			-0.00370***
			(0.000498)
Constant	0.0155***	-0.0271***	0.0365***
	(0.00309)	(0.00495)	(0.00987)
Observations	3,890	3,890	3,890
R-squared	0.000	0.030	0.043

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Note: Observations coincide with the sample of trips used in the estimation of the structural model in chapter (2). Trips are a random sample of grocery, discount store and drug store purchases as well as online purchases from the Grocer Partner and Big Tech services made by households in the 27 metro areas that contain Big Tech and Grocer Partner service users in 2015-2016. For each trip, the dependent variable takes value 1 if the retailer corresponding to that purchase is the Grocer Partner service. Coefficients represent the correlation of each variable with the probability of a consumer using that service at any point in time.

Table B.21: Effect of Offline Retail Availability on Probability of Big Tech Service Usage

VARIABLES	(OLS) Big Tech	(OLS) Big Tech	(OLS) Big Tech
Distance to Closest Grocer Partner Affiliated Store (miles)	-0.00106	-0.000702	-0.000997
	(0.000840)	(0.000880)	(0.000881)
Distance to Closest Store (miles)	0.00672***	0.00751***	0.00684***
	(0.00165)	(0.00174)	(0.00175)
Number of Grocer Partner Affiliated Available		0.000685	0.000585
		(0.000495)	(0.000495)
Number of Stores within 1 mile			-0.00318***
			(0.000769)
Constant	0.00480	-0.00694	0.0510***
	(0.00780)	(0.0115)	(0.0181)
Observations	3,890	3,890	3,890
R-squared	0.004	0.005	0.009

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Note: Observations coincide with the sample of trips used in the estimation of the structural model in chapter (2). Trips are a random sample of grocery, discount store and drug store purchases as well as online purchases from the Grocer Partner and Big Tech services made by households in the 27 metro areas that contain Big Tech and Grocer Partner service users in 2015-2016. For each trip, the dependent variable takes value 1 if the retailer corresponding to that purchase is the Big Tech service. Coefficients represent the correlation of each variable with the probability of a consumer using that service at any point in time.

Table B.22: Number of Purchases Using Online Delivery/ Year

	Big Tech or Grocer Partner	All Online retailers
Income $>$ 70K	9.26	25.59
Income [45K, 70K)	7.61	19.94
Income $<$ 45K	6.81	19.13

Table B.23: Consumer Surplus by Income Group ($): Big Tech

	Surplus/ Purchase	Surplus/ Year
Income $>$ 70K	21.36	197.79
Income [45K, 70K)	13.64	103.80
Income $<$ 45K	4.94	33.64
Weighted Average	12.85	131.20

Table B.24: Consumer Surplus by Income Group ($): Grocer Partner

	Surplus/ Purchase	Surplus/ Year
Income $>$ 70K	13.94	129.08
Income [45K, 70K)	4.77	36.30
Income $<$ 45K	1.41	9.60
Weighted Average	9.85	95.81

Note: The first table shows the household average number of purchases per year by income group. The second and third tables show the consumer surplus induced by the new services estimated by the model using estimates in column (2) table (B.34) and table (B.35). The annual values make use of each consumer's average yearly online delivery purchases.

Table B.25: Grocer Partner Firm: Dollar Value per Purchase

	Complementarity ($)	Substitution ($)
Income > 70K	15.67	1.85
Income [45K, 70K)	9.27	2.83
Income < 45K	10.24	2.34

Table B.26: Grocer Partner Firm: Dollar Value per Year

	Complementarity ($)	Substitution ($)
Income > 70K	145.10	17.13
Income [45K, 70K)	70.54	21.54
Income < 45K	69.73	15.94

Table B.27: Big Tech Firm: Dollar Value per Purchase

	Complementarity ($)	Substitution ($)
Income > 70K	0	2.50
Income [45K, 70K)	0	3.83
Income < 45K	0	3.16

Table B.28: Big Tech Firm: Dollar Value per Year

	Complementarity ($)	Substitution ($)
Income > 70K	0	23.15
Income [45K, 70K)	0	29.15
Income < 45K	0	21.52

Note: This table shows the dollar value to consumers associated exclusively with the complementarity and substitution channels relative to offline retail in the vicinity of their homes. The results presented make use of the estimates in column (2) table (B.34) and table (B.35). The annual values make use of each consumer's average yearly online delivery purchases.

Table B.29: What is the Offline 'Second Choice' When Consumers Choose Big Tech

Channel of Second Choice	Income < 45K	Income [45K - 70K)	Income > 70K
Discount Store	X	1.3%	1.94%
Drug Store	8.16%	19.48%	12.62%
Grocery Store	91.84%	79.22%	85.44%

Table B.30: What is the Offline 'Second Choice' When Consumers Choose Grocer Partner

Channel of Second Choice	Income < 45K	Income [45K - 70K)	Income > 70K
Discount Store	22.22%	9.82%	7.00%
Drug Store	1.85%	9.38%	9.73%
Grocery Store	75.93%	80.80%	83.27%

Note: Table shows substitution patterns between the two delivery services and 3 offline channels. The share of choices associated with each channel are presented when the two same-day delivery services are removed from the choice set and retailer choices implied by the model are from one of the 3 offline channels.

Table B.31: Biggest Losers: Top 'Second Choice' Retailers

Second Choice Retailers	Big Tech as Choice	Grocer Partner as Choice
Largest Online Loser	33%	35%
Largest Grocery Loser	7.22%	2.92%
Largest Discount Loser	0.31 %	3.23%
Largest Drug Store Loser	3.35%	2.92%

Note: Table shows substitution patterns between the two delivery services and retailers from 3 offline channels as well as the online channel. The share of choices associated with each channel are presented when the two same-day delivery services are removed from the choice set.

Table B.32: Switching Patterns: Evidence of Consumer Lock-in

	s' = *no subscription*	s' = *Big Tech*	s' = *Grocer Partner*
s = *no subscription*			
Fraction of Purchases	99.83%	0.16%	0.01%
s = *Big Tech*			
Fraction of Purchases	0.21%	99.61%	0.18%
s = *Grocer Partner*			
Fraction of Purchases	0.29%	0.34%	99.37%

Note: From one purchase to the next, consumers tend to repeat their platform choice. Switching is rare, representing less than 2% of all purchases. Statistics are based on platform user purchases in 2015-2017 across online and offline channels. s is the consumer's subscription status inferred from past purchases and s' is the subscription choice inferred from the current purchase choice.

Table B.33: Switching Occurs When Subscriptions Expire

	To *Big Tech*	To *Grocer Partner*	To no Subscription
Switch from *Big Tech*	-	428 days	304 days
Switch from *Grocer Partner*	285 days	-	82 days
Obs 2,411			

Note: This table shows that consumers that do switch between services, do so around the time their subscription is expected to expire. I calculate the average number of days since the consumer first uses the service to when the consumer switches. Switching occurs approximately one or two years after the first use. Grocer Partner can be used without a subscription and, consequently, switching can occur earlier.

Table B.34: Demand Model Estimates: Demographics

	(1)	(2)
Big Tech * Under 30	2.39	3.09
	[2.36, 2.44]	[3.04, 3.14]
Big Tech * Income [45K - 70K)	7.36	10.85
	[7.24, 7.47]	[10.65, 10.98]
Big Tech * Income > 70K	10.51	7.84
	[10.34, 10.68]	[7.64, 7.94]
Big Tech * Single Female	0.228	0.543
	[0.225, 0.232]	[0.532, 0.551]
Grocer Partner * Under 30	2.15	1.66
	[2.12, 2.19]	[1.62 1.69]
Grocer Partner * Income [45K - 70K)	0.00132	0.00081
	[0.00130,0.00134]	[0.00079, 0.00082]
Grocer Partner * Income > 70K	9.10	13.25
	[8.96, 9.25]	[12.97, 13.40]
Grocer Partner * Single Female	0.79	0.36
	[0.78, 0.80]	[0.35, 0.36]
Retailer Fixed-effects	YES	YES
η	NO	YES

Table B.35: Demand Model Estimates: Household Location, Travel Cost and Income-Price Elasticity

	(1)	(2)
Big tech * Retailers < 1 mile	-0.181	
	[-0.185, -0.179]	
Big Tech * Retailers < 5 miles	-0.041	
	[-0.040, -0.041]	
Big Tech * Closest Store (miles)		0.461
		[0.452, 0.467]
Grocer Partner * Retailers < 1 mile	-0.979	
	[-0.995, -0.963]	
Grocer Partner * Retailers < 5 miles	0.335	
	[0.329, 0.340]	
Grocer Partner * Nb G Partners		1.428
		[1.400, 1.444]
Grocer Partner * Closest Store (miles)		0.342
		[0.335, 0.346]
Income * Price (10K)	0.572	0.569
	[0.563, 0.581]	[0.558, 0.568]
Travel Cost ($/mile)	0.56	0.55
	[0.55, 0.57]	[0.55, 0.56]
Retailer Fixed-effects	YES	YES
η	NO	YES

Note: This table shows demand coefficient estimates in dollar value of consumer demographic and location characteristics interacted with the retailer fixed-effects for Big Tech and Grocer Partner. It also shows coefficient estimates for consumers' travel cost in dollar value per mile and for the interaction term between income and bundle price, showing how higher income users are less sensitive to prices. Estimates are based on a random sample of 3,890 visits across all 4 channels: Grocery, Discount Store, Drug Store and Online Shopping. Both specification include 35 retailer chain dummies (fixed-effects). Confidence intervals of 95% from bootstrapping of approximated outer distribution.

Table B.36: Demand Model Estimates: Switching Costs

	s' = *Big Tech*	s' = *Grocer Partner*
s = *no subscription*	\$ 4.50	\$ 13.87
	[4.13, 5.12]	[12.89, 14.92]
s = *Big Tech*	-	\$ 11.05
		[8.13, 11.93]
s = *Grocer Partner*	\$ 6.74	-
	[6.24, 7.54]	
Subscription Fixed Cost	0.9	0.99
	[0.76, 0.91]	[0.97, 1.26]

Note: This table shows demand coefficient estimates of switching costs across services. Costs include all fees in a per-purchase base as well as any other type of switching costs implicit in consumers' decisions. Confidence intervals are computed using the confidence intervals on utility coefficients. For each bound on first set of parameters, I solve for the second set of moments to get bounds on switching costs. Estimates are based on a random sample of 3,890 visits across all 4 channels: Grocery, Discount Store, Drug Store and Online Shopping. Both specification include 35 retailer chain dummies (fixed-effects). Confidence intervals of 95% from bootstrapping of approximated outer distribution.

Table B.37: Law of Motion of Subscribers With (left) and Without Switching Costs (right)

	$s'=0$	$s'=B$	$s'=G$
$s=0$	0.9804	0.0134	0.0062
$s=B$	0.0074	0.9883	0.0042
$s=G$	0.0114	0.0048	0.9838

	$s'=0$	$s'=B$	$s'=G$
$s=0$	0.6015	0.1082	0.2902
$s=B$	0.0227	0.6304	0.3469
$s=G$	0.2124	0.3142	0.4733

Note: Transition probability matrices across subscription choices $s \in \{$No Subscription (0), Big Tech (B), Grocer Partner (G)$\}$ predicted by the demand model when consumers have (left) and don't have (right) switching costs. Probabilities are calculated using all consumers in sample, across all markets.

Table B.38: Flow Profit Parameters

	Big Tech
Constant	-0.356
	(0.189)
FC Size (sq-ft)	-19.298
	(1.116)
Market Pop Density	71.118
	(8.615)

	Grocer Partner
Constant	26.958
	(1.034)
Partners (Fixed Cost)	-0.068
	(0.005)
Market Pop Density	1.278
	(0.505)
Partners (Revenue)	18.748
	(8.514)

Note: This table shows coefficient estimates of firms' flow profit parameters. Revenues are the firm's customer base times an average revenue per customer previously calibrated based on subscription fees and a gross margin on consumers' mean purchase expenditures.

Table B.39: Entry Costs

Big Tech	-72.746
	(12.455)
Big Tech * Time	9.822
	(1.469)
Grocer Partner - First Entry	-5.244
	(0.821)
Grocer Partner * Time	35.239
	(3.924)
Grocer Partner - Expansion	-5.548
	(2.487)

Note: This table shows coefficient estimates of firms' entry costs with linear time effect on those costs. Entry costs are high for Big Tech and much lower for Grocer Partner. For both firms, entry costs fall over time.

Table B.40: Strategic Entry Timing versus Commitment

	Lock-in and Competition	Pre-Commitment
Average Time to Entry *Big Tech*	3.55	4.68
Average Time to Entry *Grocer Partner*	3.97	5.20
Total Number of Obs	169	169

Note: This table shows that, in the competitive equilibrium with lock-in, Big Tech enters markets on average 3.55 years after the beginning of the game in June 2012. Grocer Partner's entry and expansion decisions take on average 3.97 years to occur after the beginning of the game in this equilibrium. For both firms, the average time taken to enter is approximately 1.2 years later when they commit to entry times.

Table B.41: Early versus Late Entry Payoffs

%Δ Average Payoff *Big Tech*	10.84 %
%Δ Average Payoff *Grocer Partner*	31.34%
Number of Delayed Entries *Big Tech*	79
Number of Delayed Entries *Grocer Partner*	66
Total Efficiency loss	20.17%
Total Number of Obs	169

Note: This table shows firms' gain from delayed entry in terms of percentage payoff change and the number of markets in which entry would be delayed in the pre-commitment equilibrium relative to the equilibrium with lock-in and competition.

Table B.42: *Big Tech* Acquires Brick-and-Mortar Grocery Chain: Entry Timing Counterfactual

	Post-Merger (2018-2019)	No Merger
Average Time to Entry *Big Tech*	6.18	8.69
Average Time to Entry *Grocer Partner*	4.73	6.87
Total Number of Obs	30	30

Note: This table shows how the acquisition between Big Tech and the grocery chain induced faster entry across new markets entered after June 2017 for both firms relative to the counterfactual where the acquisition did not occur. Big Tech enters these markets on average 6.18 years after the beginning of the game in June 2012. The results show that Grocer Partner reacts to this acquisition entering over 2 years earlier than it would otherwise to benefit from consumer lock-in.

Table B.43: *Big Tech* Acquires Brick-and-Mortar Grocery Chain: Consumer Welfare Gains and Producer Losses

%Δ Average Payoff *Big Tech*	10.05 %
%Δ Average Payoff *Grocer Partner*	6.41 %
Number of Anticipated Entries *Big Tech*	28
Number of Anticipated Entries *Grocer Partner*	27
Total Loss of Early Entry	624 ($ M)
Total Consumer Welfare Gain	846 ($ M)
Total Number of Obs	30

Note: This table shows how the timing of entry with and without the acquisition compare in terms of costs for firms and consumer welfare. Loss of early entry includes Grocer Partner's cost of accelerating entry due to the acquisition and the cost Big tech would have incurred with the post-merger entry timing with its original cost structure. The latter approximates the portion of the value payed for the acquisition associated with increased entry speed ability. Consumer gains are from early entry across new markets.

Table B.44: Merger between *Big Tech* and Grocer Partner: Monopoly Counterfactual

Monopolist's Average Time to Entry	10.10
Share of Markets with *Big Tech* Business model	20.64%
Efficiency Gain	1.66 ($ B)
Welfare Loss	2.04 ($ B)
Total Number of Obs	169

Note: This table shows how a potential merger between Big Tech and Grocer Partner would induce slower entry timing. it would take the monopolist on average more than 6 years longer to enter markets that received either or both services during 2012-2017. The monopolist chooses the most profitable business model by market. Gain from monopoly accounts for cost savings from lack of early entry and efficiency gains due to scale economies.